PIRE: Partnerships for International Research and Education:

OISE-0968369: *Bilingualism, mind, and brain: An interdisciplinary program in cognitive psychology, linguistics, and cognitive neuroscience*

(2010-2015)

Pennsylvania State University
Center for Language Science
(http://www.cls.psu.edu)

PI: Judith Kroll
Co-PIs: Paola Dussias
Ping Li
Janet van Hell

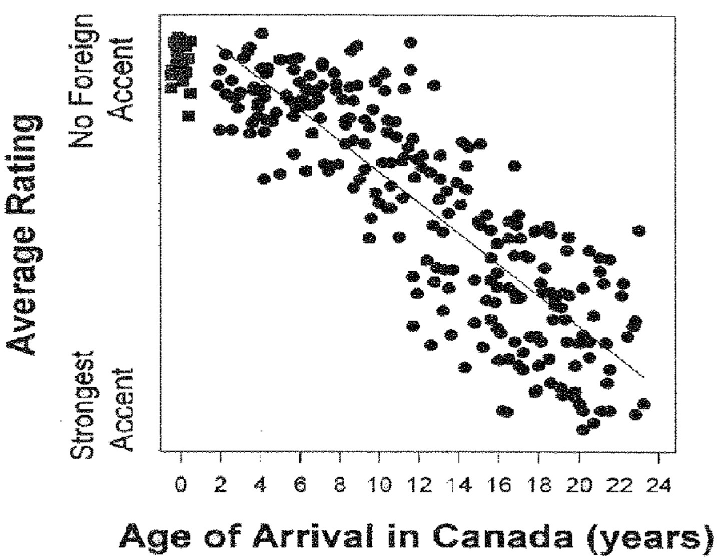
More people in the world are bilingual than monolingual.

But until very recently, most research on language and cognition examined only monolingual speakers of a single language and typically speakers of English as the native language.

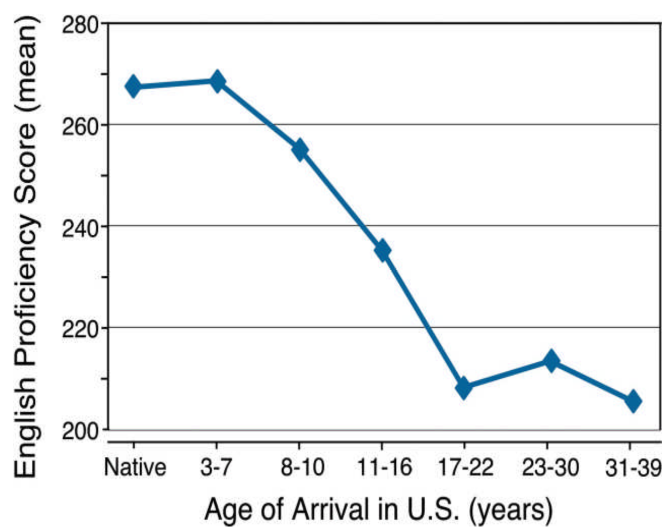
Why have bilinguals been considered special despite the large number of people in the world who speak more than one language?

There are many reasons but a key observation is that learning an L2 past early childhood is a difficult task with mixed outcomes.

Even highly successful late L2 learners speak with an accent and appear to fail to acquire subtle aspects of the L2 grammar.



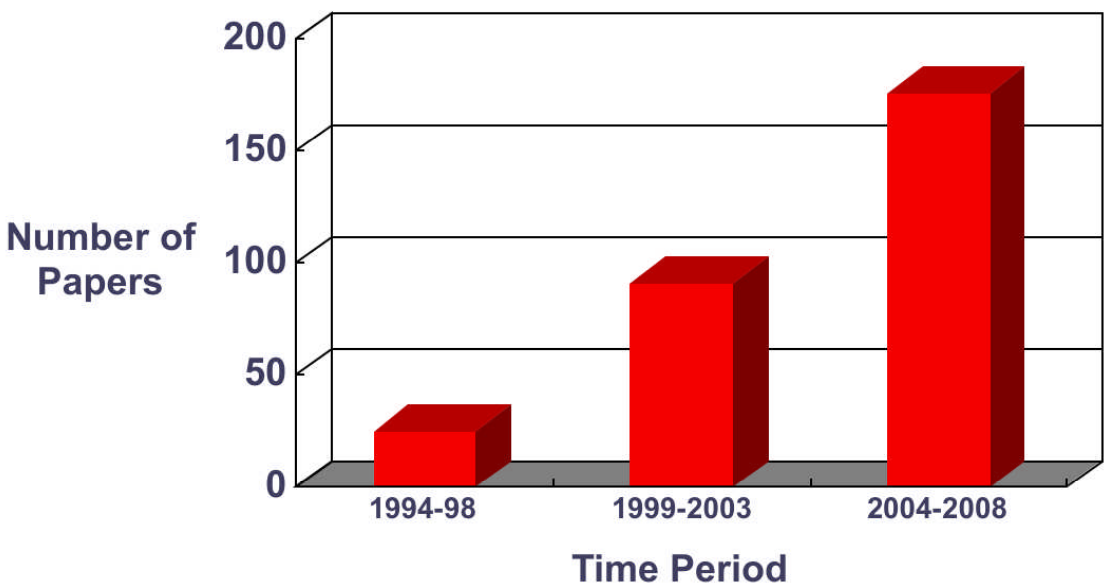
Flege et al. (1995)



Johnson & Newport (1989)

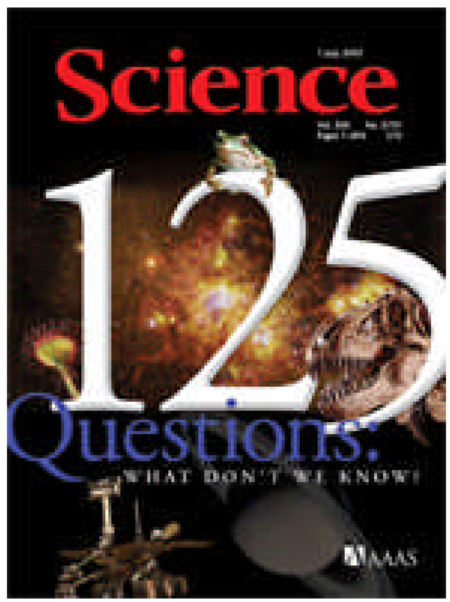
In the past 15-20 years, that situation has changed:

Papers published on “bilingual language processing” since 1994



[Data from the Web of Science]

On the 125th anniversary of the journal *Science*, Kennedy and Norman (2005) identified the biological basis of second language (L2) learning as one of the top 125 questions to be answered in the next 25 years of research:



❖ Bilingualism and second language learning provide a lens for researchers to examine aspects of the underlying cognitive architecture that are obscured by native language skill when investigating language learning and language performance in the first or dominant language only. We would not know that these changes occur unless there was another language.

❖ The bilingual's two languages sometimes converge and sometimes compete. Identifying the conditions that give rise to each of these outcomes reveals the constraints and plasticity that underlie language representation and its cognitive and neural underpinnings.

❖ *Bilingualism is a tool for cognitive scientists*

Research Collaborations here and abroad:

Penn State University

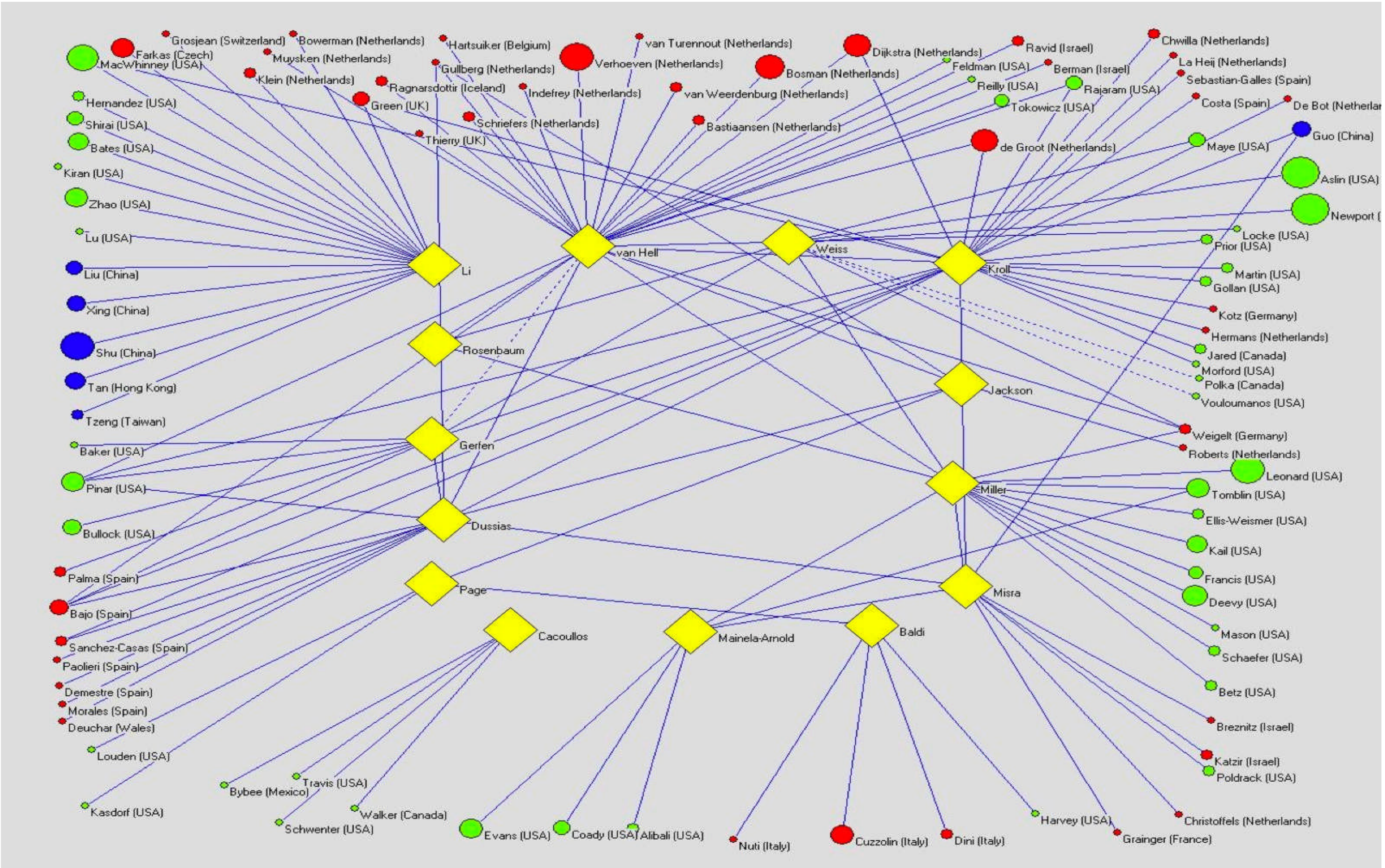
University Park, PA

The Netherlands

Spain
Germany
UK
China

Bilingualism takes different forms in different places

The Penn State Center for Language Science Bilingualism Network



The Center for Language Science PIRE Project:

Bilingualism, mind, and brain: An interdisciplinary program in cognitive psychology, linguistics, and cognitive neuroscience

A network for research and training:

Domestic Partners:

Haskins Laboratories, Yale University
VL2 NSF Science of Learning Center, Gallaudet University

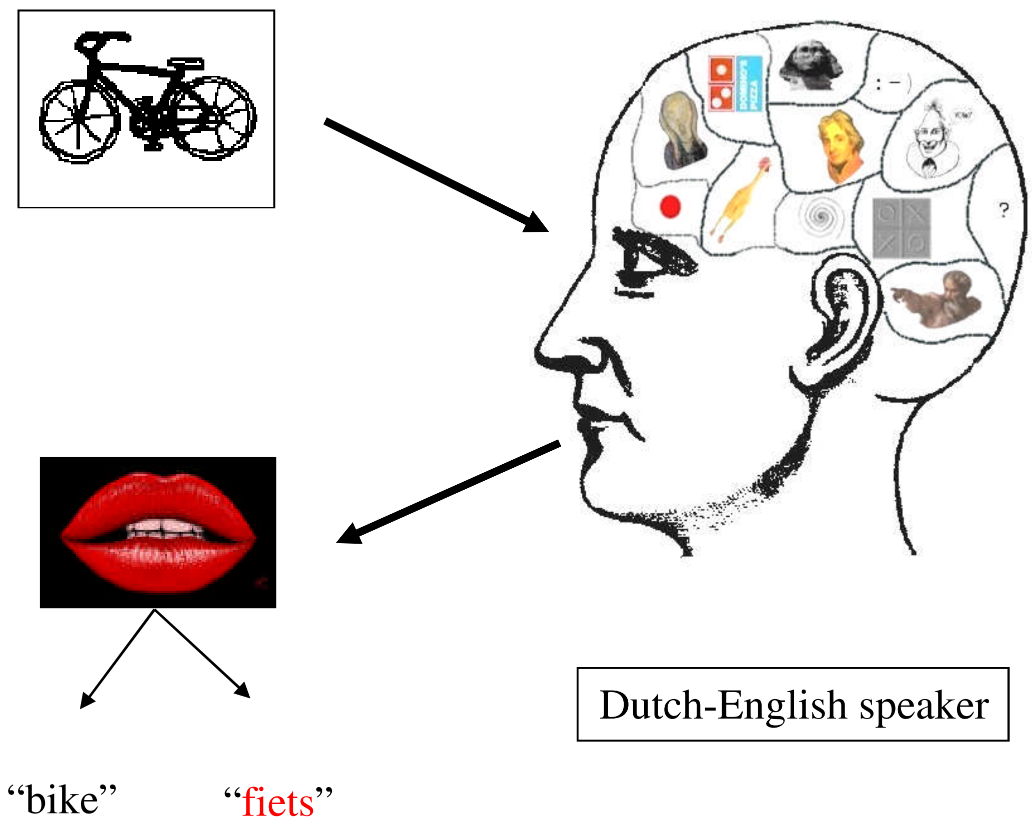
International Partners:

Radboud University, Nijmegen, The Netherlands
Max Planck Institute, Leipzig, Germany
University of Granada, Granada, Spain
University of Pompeu Fabra, Barcelona, Spain
ESRC Centre for Research on Bilingualism, Bangor, Wales
Beijing Normal University, Beijing, China
University of Hong Kong, Hong Kong, China

The Center for Language Science PIRE

- **Science**
  - Cross-disciplinary: Psychology, Linguistics, Neuroscience
  - Type of Bilingualism: Similar and different languages in grammar, script, modality
  - Context of Language Experience
- **Training**
  - Undergraduate, graduate, postdoc and early career faculty research abroad
  - Expand domestic collaborations to enable international research training
  - Enhance professional development experiences

The bilingual is a mental juggler: Both languages appear to be active regardless of the requirement to use one language alone:



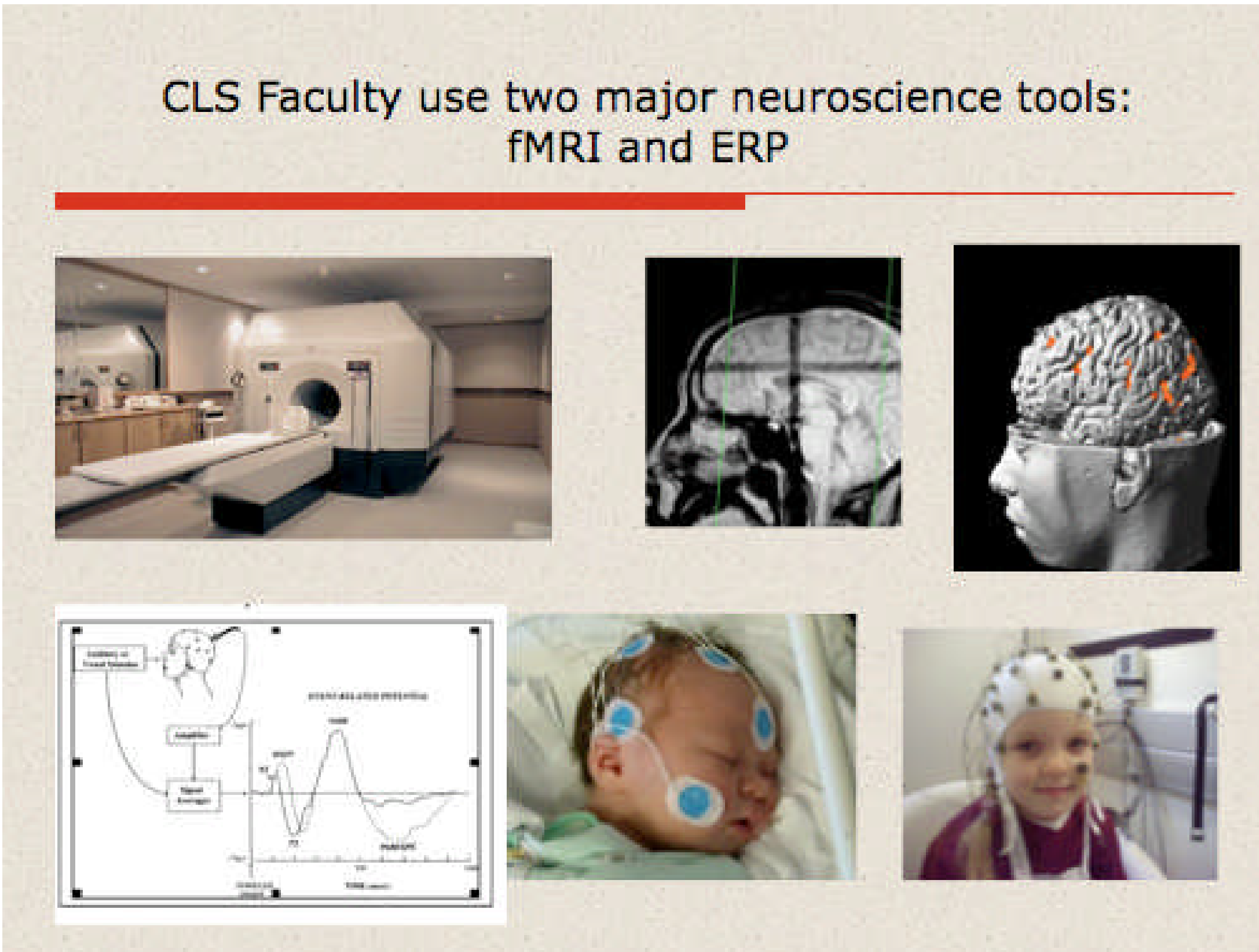
Bilinguals often code switch between the two languages in the middle of a sentence but rarely make the error of speaking the unintended language

What is the consequence of parallel activity and competition across the bilingual's two languages? The hypothesis is that mental juggling creates expertise.

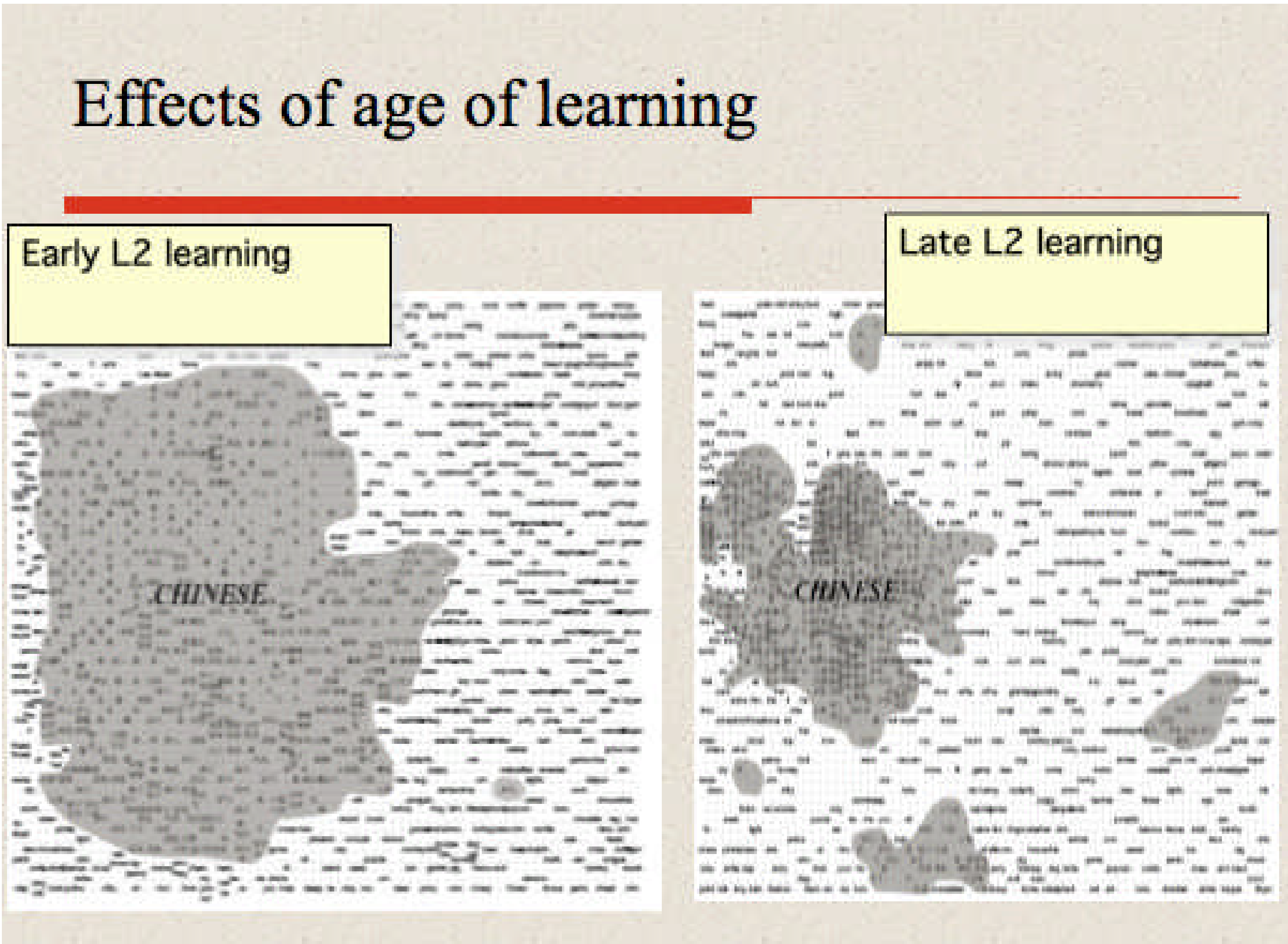
Bilingualism appears to confer specific cognitive benefits to executive function and attention to enable bilinguals to:

- ignore irrelevant information
- resolve conflict among competing alternatives
- minimize the costs associated with task switching

Methods to investigate language learning and language processing include behavioral measures, e.g., eye tracking and acoustic analyses of spoken language, and also neuroscience methods.



Computational models of language learning



Comparative approaches to language learning

Is statistical learning species-specific?

Cotton-top tamarins
(New World monkey)

Comparison across languages and across language experience

Morford et al. (under review): Replicate Thierry & Wu (2007) with ASL-English bilinguals making semantic relatedness judgments in English, the L2

Instead of repeating Chinese characters, we now have ASL translations of English words that have a “phonological” form relation or not

movie

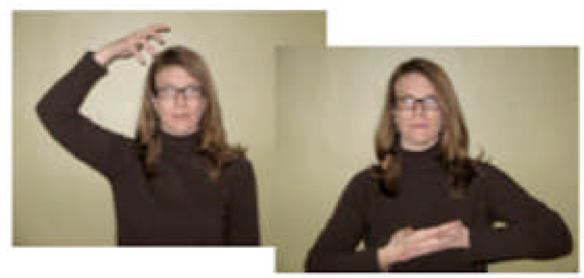
paper

Phonologically related in ASL

lion

baby

Phonologically unrelated in ASL



Deaf signers activate ASL translations while reading in English

To capture the mechanisms that enable or restrict language learning and that account for proficient bilingual performance and its cognitive consequences, we need a **comparative approach to bilingualism** that exploits different methods, the special properties of different language pairings, and different language learning contexts but that share common ground.

We and our PIRE partners share **common ground** in that we utilize similar methods, making our labs fundamentally interchangeable with respect to the basic science.

The topic of bilingualism quite naturally draws students who already have **language training** and are often bilingual themselves.

This common ground enables research training and sustained collaboration because it is **mutually beneficial**.

Programs for training:

- ❖ **Undergraduate** summer research study abroad:
  8 undergraduates each summer

- ❖ **Graduate** research internships

  Dual Title Doctoral Degree in Language Science

  Psychology, German, Spanish, Communication Sciences
  and Disorders

  Proseminar in the Language Science of Bilingualism

- ❖ **Postdoctoral** and **early career faculty** research abroad

Leveraging PIRE resources to create infrastructure

❖ **PIRE Visiting Language Neuroscience Scholar Program**

❖ **Virtual Colloquium Series** with our international partners: Students can meet our PIRE partners prior to travel abroad

❖ Annual **Young Language Scientist Colloquium** organized by graduate students

Graduate students have organized an independent meeting **R-ticle** to share methodological skills and discuss papers

❖ Support for **international students** at Penn State to pursue research abroad and for students at the partner sites to travel to Penn State

❖ **International visitors**

Planned PIRE initiatives

- **PIRE website**

- **Joint symposia at professional meetings:** The first set of proposals were submitted to the International Symposium on Bilingualism (ISB8) to be held in Oslo, Norway in June 2011

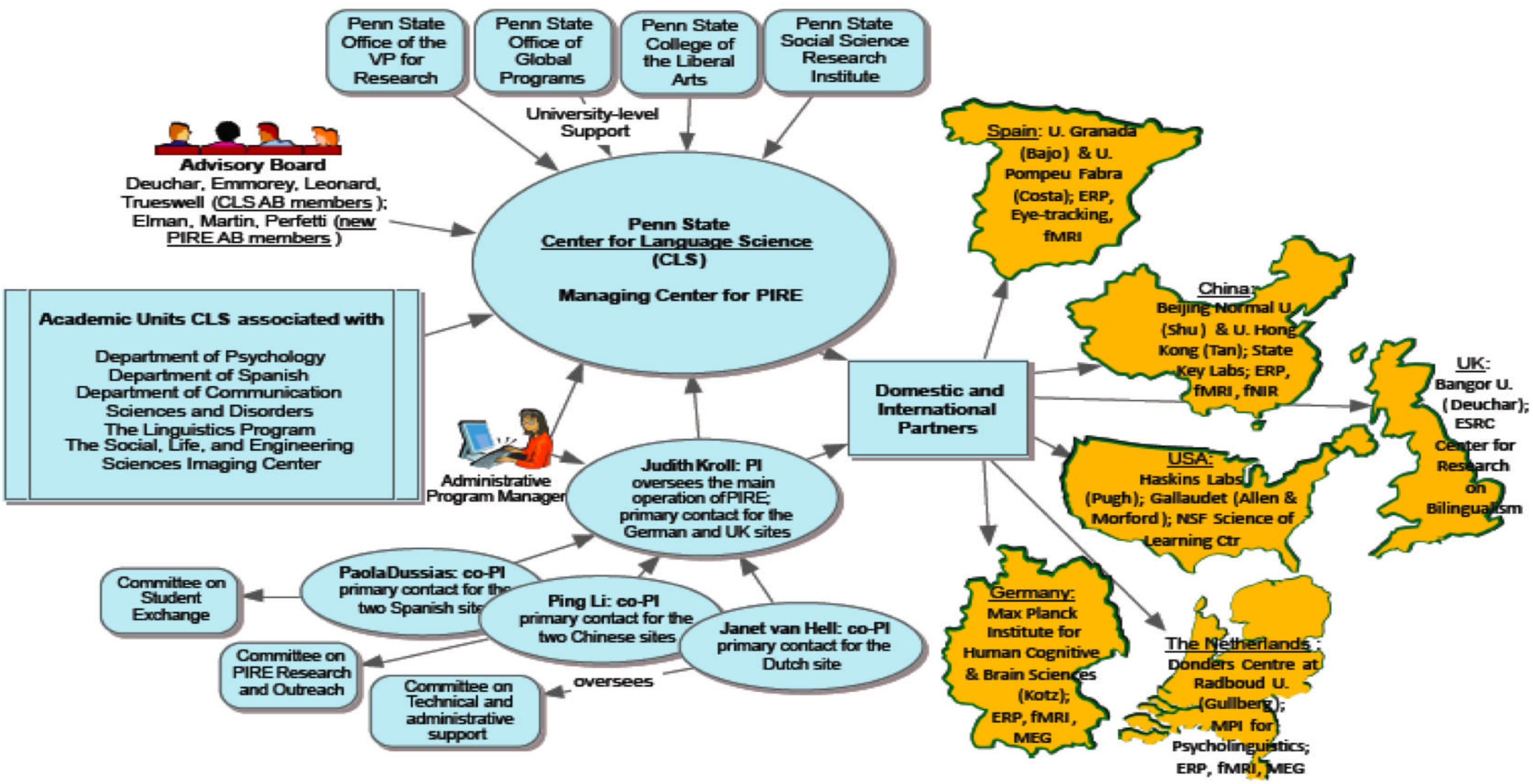
- **Bilingualism Bulletin**

- **PIRE research conference**

- **Research abroad blogs**

- **Bilingualism Summer Schools**: To be held twice during the PIRE, once at Penn State and once in Granada

Management: Putting the pieces of the PIRE together



Some benefits of collaborative networks for research and training:

1. **Data collection** (in both directions: we assist our colleagues who work in locations in which bilingualism is more prevalent by providing monolingual controls)

2. **Professional development** for graduate students: Visit host laboratories, give research talks, interact with research mentors, acquire complementary technical skills, establish an international network of young researchers

3. **Exchanges** in both directions: Steady stream of visitors increases diversity at the home institution

4. **Diversity breeds diversity**: Undergraduate research students who are themselves bilingual are likely to seek out research opportunities in this context

[redacted]

The words of our president on encouraging bilingualism:

http://www.youtube.com/watch?v=BZprtPat1Vk

Thank you!

The Science of Learning University of Queensland, Australia

Robert Colvin
robert@itee.uq.edu.au

Overview

Established officially in June 2010

Research focus: Attention

- Builds on strengths at UQ
- Relevant to the classroom
- Underlies memory storage
- Appears to involve multiple regions of the brain
- Complementary to research at other SLCs

The Centre

Directors:

- Pankaj Sah, QBI
  Professor of neurophysiology
- Ottmar Lipp, School of Psychology
  Professor of Psychology (Emotion and Learning)

Advisory Panel:

- Perry Bartlett, QBI (Director)
  Professor of neurophysiology
- Professor Deborah Terry, Deputy Vice-Chancellor

Other participants

- Cognitive neuroscience: Prof. Jason Mattingley
- Brain imaging: Prof. David Ruetens
- Neurophysiology: A/Prof. Bruno van Swinderen
- Mathematics education: Prof. Merrilyn Goos
- Cognitive psychology: Dr Paul Dux
- Computational neuroscience: Dr Robert Colvin (me)
  - (Background: theoretical computer science and complex systems)

Collaboration with
Australian Council for Educational Research (ACER)

- Conduit for testing research outcomes in the classroom
- Partner in feeding teacher input back to laboratory

Proposed collaborative approach

Each discipline involved (eg. neurophysiology, psychology) answers the same specific research question using own techniques

Synthesis of data occurs through two interfaces:

- Brain imaging
- Models and simulations

Successful trials are adapted for the classroom

History

- Can neuroscience make an impact in the classroom
- Myself hosted by Soo-Siang, CELEST, TDLC, Feb. '09
- Soo-Siang visited QBI, April '09
- Scoping of centre, collaborators
- Seed funding secured June '10

Outlook:

- Funding from State and Federal Governments.

Symposium on Attention

July 2011 (tentative)
The University of Queensland
Brisbane, Australia

Speakers from

- Neuroscience
- Psychology
- The teaching profession
- Government bodies

Please contact me for more details if interested.

Translation in the Science of Learning Centers

Brief Introductory Comments

Broad meanings of "translation" and "translation research" reflected in the presentations

Learning research and education research: overlap and differences reflected in the presentations

A useful framework based on focusing on improvements in education as a complex system
(Maroulis et al. Science Oct. 1st, 2010)

"mechanism based" *(micro-level)*
"effects based" *(macro-level)*

Translational Work at CELEST and LIFE

CELEST

* Heather Ames Versace: The applied neuroscience of learning
* Jonathan Brumberg: Brain-computer interfaces for communication
* Massimiliano Versace: Brain-inspired computing

LIFE

* Roy Pea: Augmenting educational designs with social learning
* Bill Penuel: Curriculum design studies focused on leveraging personal relevance and social practices in elementary science
* Dan Schwartz: Different models of the relation between research and translation

Translational Work at PSLC and SILC

PSLC:

* Ken Koedinger: In vivo experiments and cumulative theory as keys to translation
* Vincent Aleven: From research to practice – Interactive examples and diagrammatic self-explanation in an intelligent tutoring system
* David Klahr: Classroom experiments with TED, the Tutor for Experimental Design

SILC:

* Nora Newcombe: SILC's strategy for supporting STEM education through spatial learning
* Dedre Gentner: Supporting early STEM learning with spatial analogy and language
* Ken Forbus: Translating sketch understanding from laboratories to classrooms, and back again

Translational Work at TDLC and VL2

TDLC:

* Gary Cottrell (UCSD): Overview of at TDLC
* Terri Jernigan (UCSD): A neurodevelopmental case for personalizing education
* Sean Kang (UCSD) : Distributed practice over the long-term: Should spacing be expanding or equal interval?

VL2:

* Thomas Allen (Gallaudet) : Overview of translation at VL2
* Donna Morere (Gallaudet) : Identifying factors influencing early literacy for deaf students through longitudinal study of student, family, and school characteristics

Closing Comments

Where is the research focused?

What lies behind considerations of "Fidelity" and "Adaptation"

Fidelity to the *design*
Adaptation to the *environment*

A key challenge facing education research is to integrate insights about "micro-level" mechanisms with evidence about aggregate, "macro-level" outcomes that emerge from processes of implementing those mechanisms.

On a personal note, from translation research to implementation research

Looking at education as an integrated *complex system* whose outcome is learning:

Where is the missing research?

"Adaptation" to an environment (i.e. learning within organizations)

¨Sustainability" of improved environments (i.e. learning by the educational organization)

Brain-computer interfaces for communication

SLC PI Meeting - Translational Research

Jon Brumberg, Ph. D.

[1]Department of Cognitive and Neural Systems, Boston University, Boston, MA

[2]CELEST: Center of Excelence for Learning in Education, Science and Technology

brumberg@cns.bu.edu

October 14, 2010

Outline

Brain Computer Interfaces

What is a brain-computer interface (BCI)?

A method that facilitates interaction between neural activity and a computational system

What is a brain-computer interface (BCI)?

A method that facilitates interaction between neural activity and a computational system

Input: Cochlear implant, retinal implant, cortical sensory prosthesis

Output: Motor cortical prosthesis - computer cursor, robotic limb, communication/typing, speech synthesis

Other: Smart limb prostheses, deep brain stimulators, seizure pallative devices, replacement neural circuits

Electrode Technology

Microelectrodes: Chronic extracellular microelectrodes

- Neurotrophic Electrode and Blackrock (Utah) arrays for humans
- Capable of recording for 4-5 years (so far)
- Some systems wireless

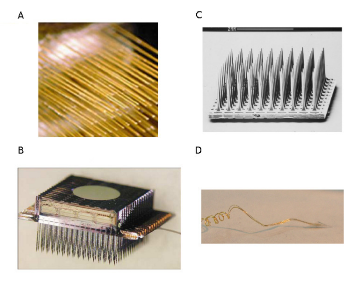
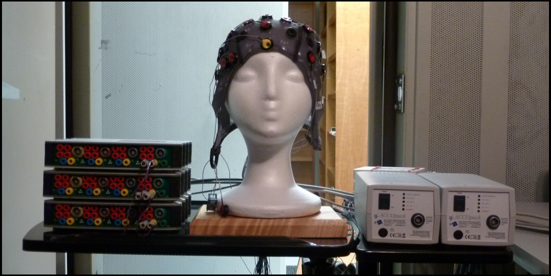


Fig. 1, Brumberg et al. (2010)
Speech Communication

Electrode Technology

EEG: Electroencephalography

- Commercial systems - no longer hand made / assembled
- Utilize active electronics to improve SNR and reduce skin impedance
- Some wireless systems



ECoG: Electrocorticography

- Middle-zone between EEG and microelectrodes
- Closer to source signal, increases SNR and higher frequency bandwidth

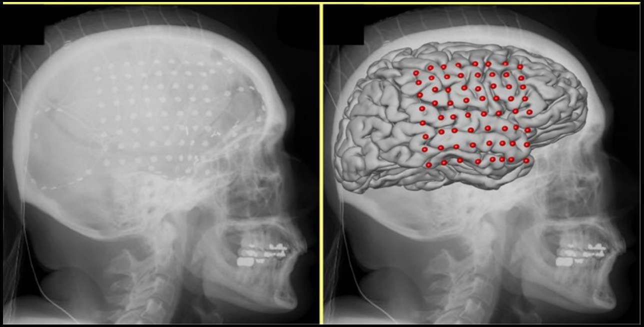


Fig. 1 from Schalk et al. (2008) *Journal of Neural Engineering*

Communication Applications

P300 Speller: Oddball, rare-stimulus event related potential (ERP)

SSVEP Speller: Visual evoked potential proportional to attended strobe stimulus

SMR Speller: Motor imagery style; cursor selection

ERD/S Speller: Motor imagery style; adaptations for binary or multi-state decision

Machine learning:

- Motor imagery; virtual keyboard
- Speech imagery; vowel comparisons

Intracortical trial: Cursor control for item selection

- Braingate
- Neurotrophic Electrode

SMR synthesis: Motor imagery style; speech sound synthesis

Requirements for Communication

1. Fast
   - Ideally fluent / real-time and progressive
   - "Texting" speed for spellers, utilize language prediction
   - Synthesis techniques within 100-200 ms of intention & transitions between sounds within 500 ms

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   - Limb motor imagery for typing (and synthesis)
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Not a requirement, but invasive vs. non-invasive a big factor

Outline

1. What is a BCI?
2. CELEST research for speech prosthesis
3. Translational steps for BCI communication

Team based research

Multifaceted approach using between and within university collaborations

- Microelectrode design
- Hardware design
- (Pre)processing and decoding techniques

- Improve Neurotrophic Electrode (with Neural Signals, Inc.)
- Animal implants (primate @ MIT; bird @ BU)

Improve	SNR and unit detection
Quantify	longevity in terms of "structural" and "functional" across species
Motivate	improvements to FDA approved design for human use

Team based research

Multifaceted approach using between and within university collaborations

- Microelectrode design
- Hardware design
- (Pre)processing and decoding techniques

Develop mobile systems for intracortical and non-invasive wireless telemetry

Current: wireless via Neural Signals, Inc. collaboration (limited bandwidth)

Future: wireless via MIT, Neural Signals collaboration for high bandwidth

- Have begun feasibility study with EEG

Team based research

Multifaceted approach using between and within university collaborations

- Microelectrode design
- Hardware design
- (Pre)processing and decoding techniques

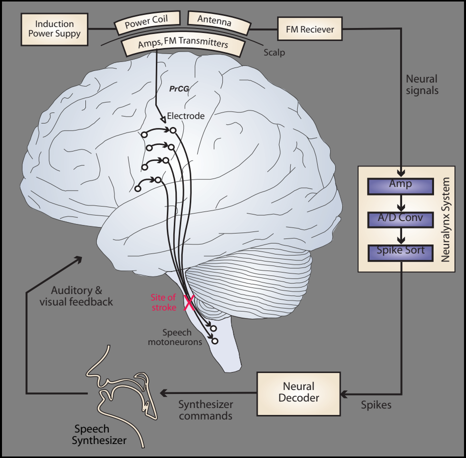
- Intracortical signals processed for: LFP (low band), MUA (high band) and spikes
- EEG / ECoG, processed for frequency amplitude, band power, instantaneous phase / frequency
- Discrete-time adaptive filtering: Kalman filter, Weiner filtering, Least mean squares filtering.
- Supervised classification: Support vector machines, discriminant analysis, logistic regression - other machine learning techniques

Team based research

Multifaceted approach using between and within university collaborations

- Microelectrode design
- Hardware design
- (Pre)processing and decoding techniques

- BCI implementation and translation



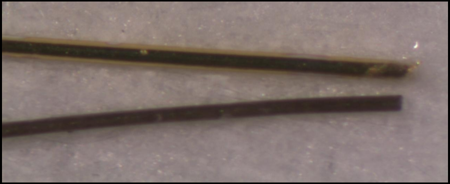
Result of interdisciplinary and collaborative research within academia and industry

Purpose

Intracortical BCI must perform reliably for extremely long durations

Current design:

- 3-4 "large" (50 μm.) gold wires
- Placed inside a 1 mm. glass cone - relatively distant (300 μm.)
- Filled with growth factor to encourage axon growth



Microelectrode design & evaluation

Purpose

Intracortical BCI must perform reliably for extremely long durations

Current design:

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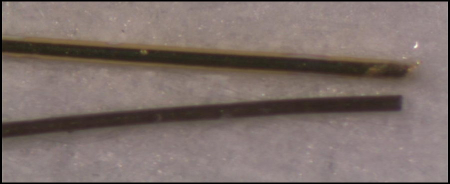
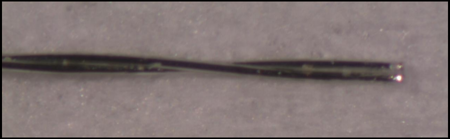


New design:

- 3 "small" (25 $\mu m.$) pairs of platinum wires: stereotrode
- Reduce spatial smoothing with smaller surface area
- Able to coregister putative spikes across two channels
- Modify cone to 300 $\mu m.$ polyimide tube for bird implants



Motor Approach to Communication BCI: intracortical

Key concept

Speech is a motor behavior

History

- Leverage rigorous motor BCI foundation to speech problem
- 30-years of intracortical and EEG research for motor behavior

Theory

- Neurocomputational model of speech production (DIVA) developed in our lab
- Makes specific hypotheses about neural architecture during speech production
- Verified via experimental results with fMRI and articulometry

Key concept

Speech is a motor behavior

Translation: from theory to application

(0528_Full_NEW.mp4)

./Movies/0528_Full_NEW.mp4

Motor Approach to Communication BCI: intracortical

Key concept

Speech is a motor behavior

Translation: from theory to application

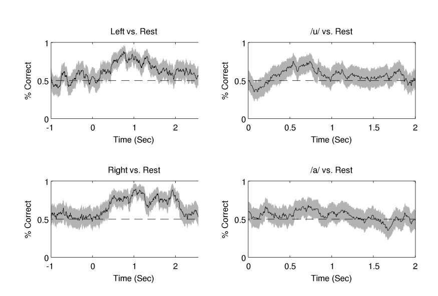
Performance increased from 45-70% (max 89%) within each 2 hour session

Learning BCI control requires instantaneous, real-time feedback.

- Need to retrain every day, working on long-term, adaptive solutions

Method: Whole head EEG (though primarily sensorimotor rhythms)
Objective: To decode speaking intent; alternatively "voicing" detection

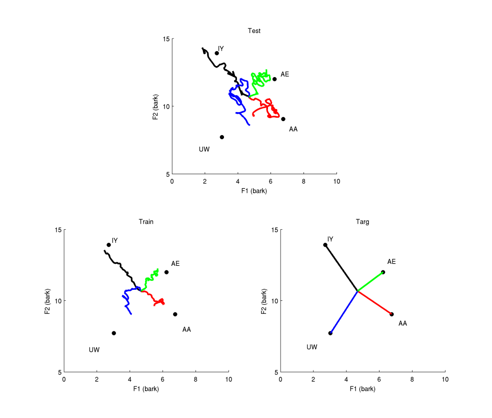
- Ask subjects produce a known speech sound for a specified duration (visual cue)
- Use SMR band power to determine production from rest
- Needed for fluent speech:
  - pauses are halmarks of speech
  - turn on/off communication device



E. Stephen, pilot results

Method: Whole head EEG (though primarily sensorimotor rhythms)
Objective: control a 2D vowel synthesizer

- Ask subjects to produce a known speech sound for a specified duration (visual or auditory cue)
- Use discrete-time adaptive filtering techniques of SMR band power to predict instantaneous vowel estimate
- supply real-time synthesis and feedback



J. Brumberg, pilot results

Outline

AAC: Augmentative and Alternative Communication

- The primary solution for communication by those with many speech disorders: akinetic mutism (ALS), cerebral palsy, etc.
- Have already uncovered optimal human computer interaction designs
- Utilize muscle activity, eye gaze
- Objective: Add EEG / BCI channel
  - Translation from lab to users

Industry-Academia Collaboration

New Collaboration

Began partnership with Dynavox Technologies in Summer 2010

- Dynavox is a world leader in AAC device development and distribution
- CELEST Catalyst to assist development of statement of work and university sponsored research project
- Sponsoring funding graduate student and travel to academic conferences.

Thank You!

Supported in part by CELEST, a National Science Foundation Science of Learning Center (NSF SMA-0835976) and by the NIH (R01-DC00763 and R44-DC007050)

CELEST
Center of Excellence for Learning in Education, Science and Technology

Collaborators

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Rahul Sarpeshkar

Dynavox Technologies
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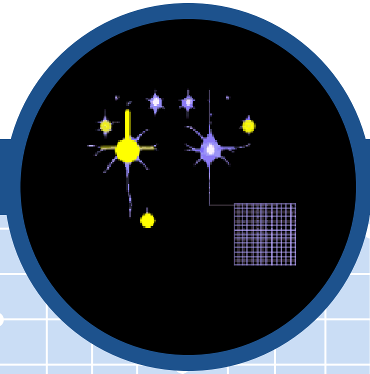


Center of Excellence for Learning in Education, Science and Technology

Neural designs for nanochip applications

MASSIMILIANO VERSACE

CELEST & Technology

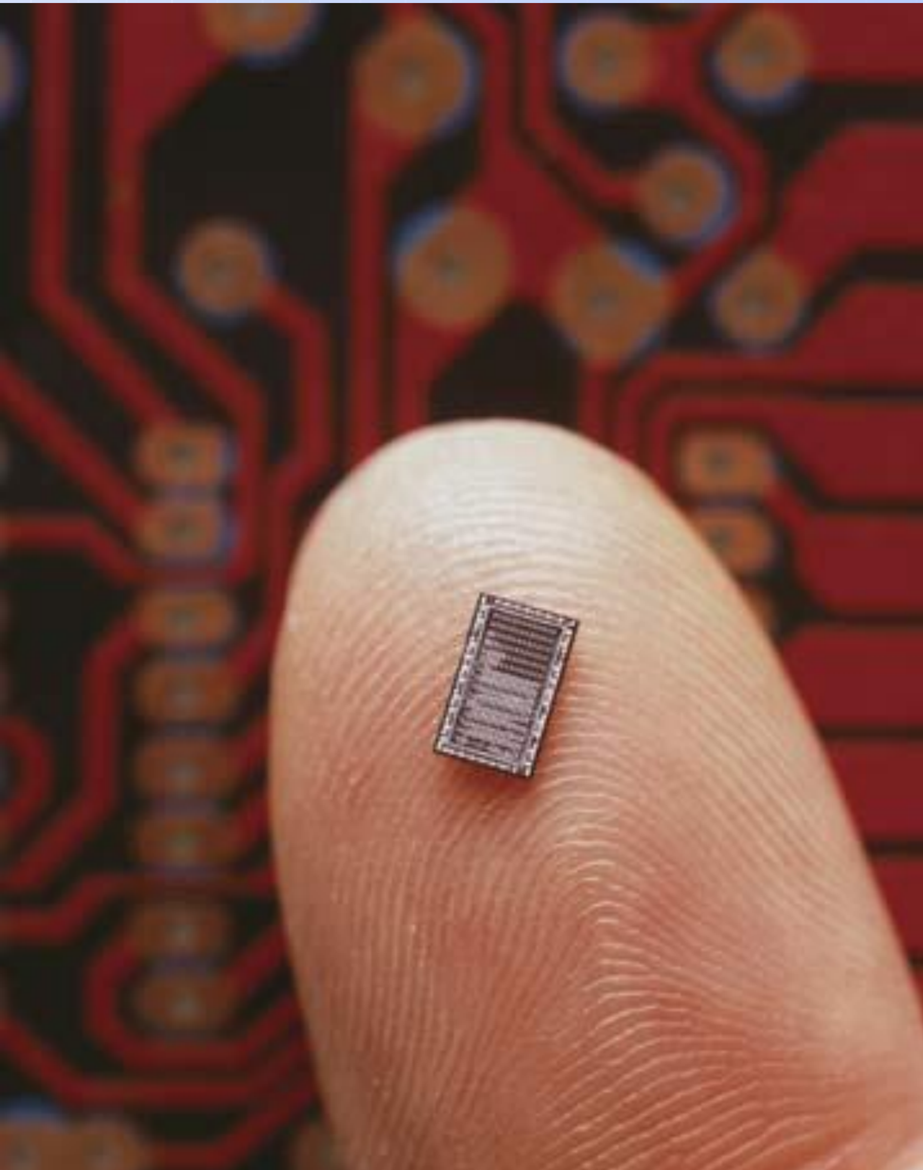
Mission Statement

The CELEST technology effort promotes translational research through

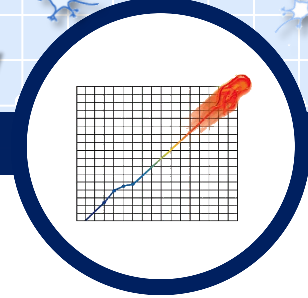
- industry partnerships
- education, and
- outreach

to facilitate real-world technological applications of CELEST research

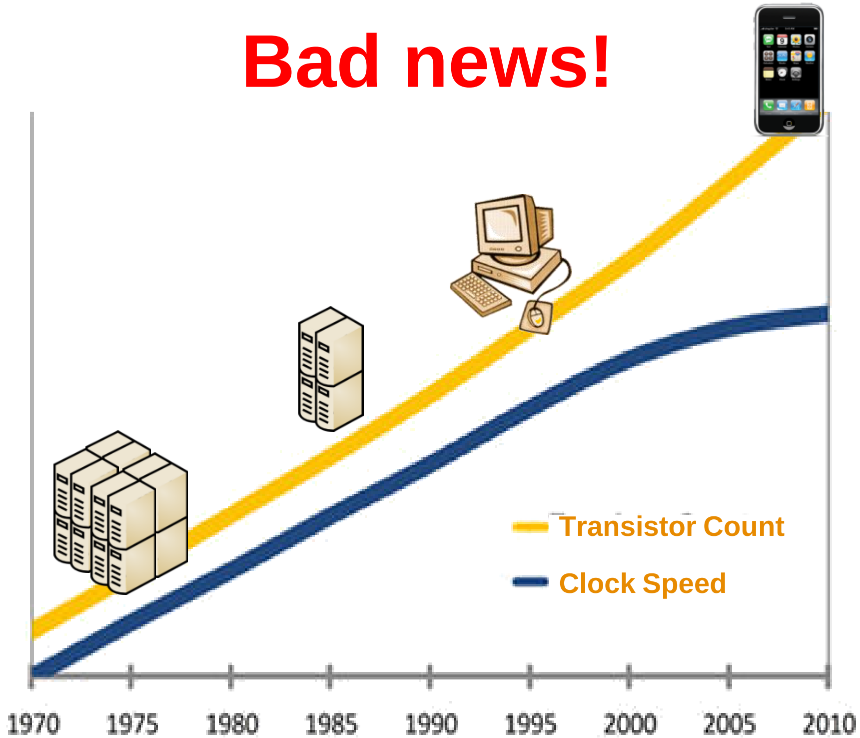
What is the problem?



Motivation: Moore's Law



Bad news!



clock speed
of individual transistors
is **leveling off**

Von Neumann architecture

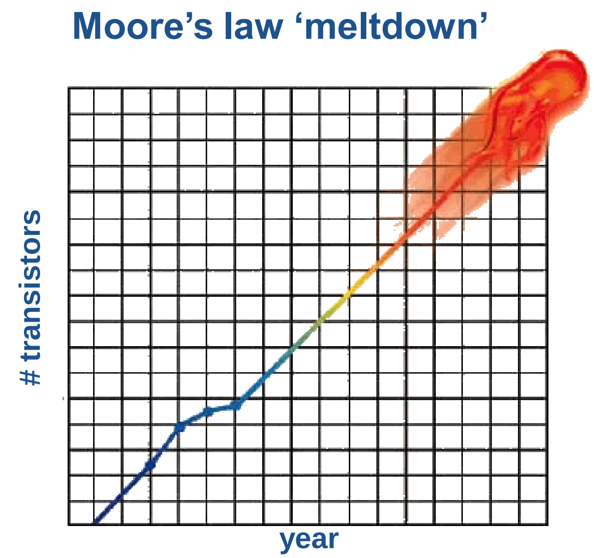
Computers **physically separate** the functions of computation and data storage

Our brains do not: synapses!

How could a computer with **merged** computation and data storage function?

The DARPA SyNAPSE project

The DARPA SyNAPSE (Systems of Neuromorphic Adaptive Plastic Scalable Electronics) program seeks to find a solution to the **imminent failure of Moore's law for conventional chips**



SyNAPSE goal: **"enable electronic neuromorphic machine technology that is scalable to biological levels"**

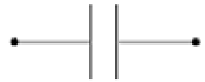
traditional algorithms perform **poorly** in the complex, real-world environments where biological agents **thrive**

vs.

traditional microprocessors are **extremely inefficient** at executing highly distributed, data-intensive algorithms

The discovery of memristors

RESISTOR
$v = \mathcal{R}\, i$

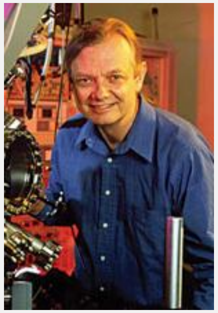


CAPACITOR
$q = \mathcal{C}\, v$

INDUCTOR
$\varphi = \mathcal{L}\, i$

MEMRISTOR
$\varphi = \mathcal{M}\, q$

Leon Chua
1971

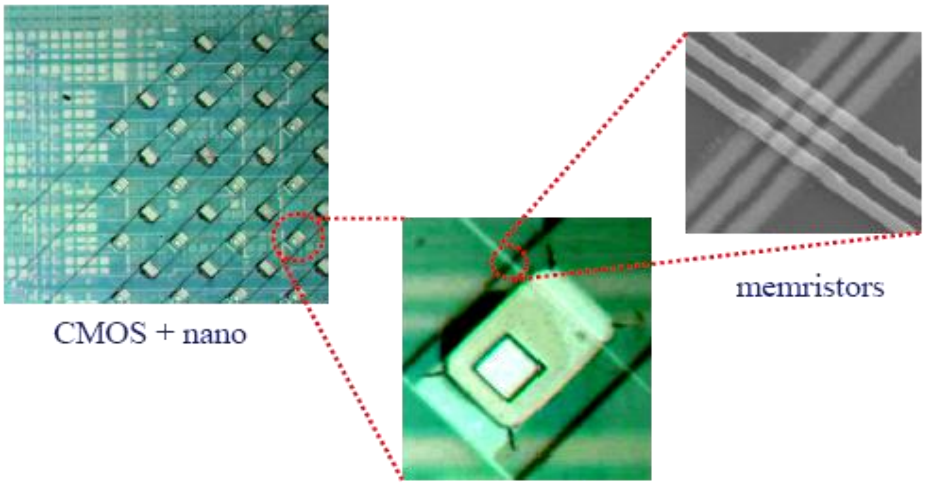


Stan Williams

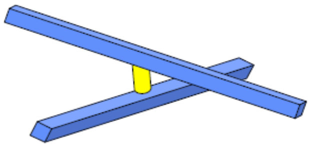
Greg Snider

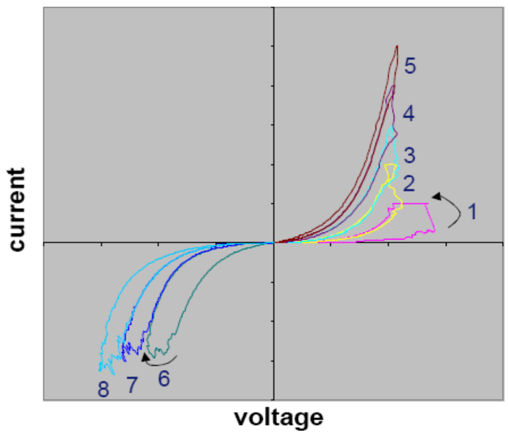
2008

Information & Quantum Systems Lab

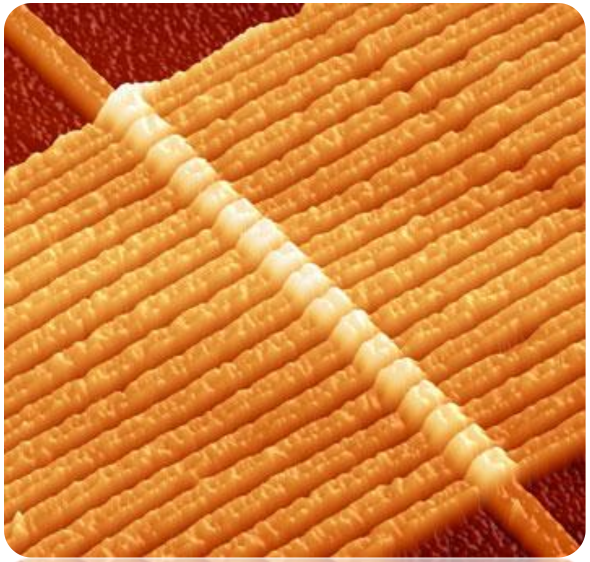


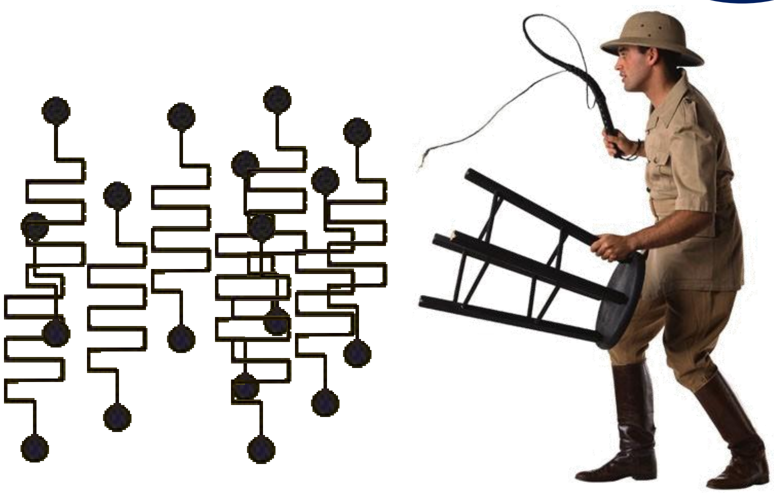
3x3 crossbar
(100 nm nanowires)





Taming the beast





Memristors are "crummy" devices

What are very compact but imprecise and unreliable nanoscale devices good for?

BUILD BRAIN-LIKE CHIPS!

When the device is built, it will have unknown dynamics

CELEST researchers bring expertise with large-scale, biologically motivated neural systems that perform behavioral tasks

The DARPA SyNAPSE project

Hardware

Architectures

SyNAPSE

Large scale simulations

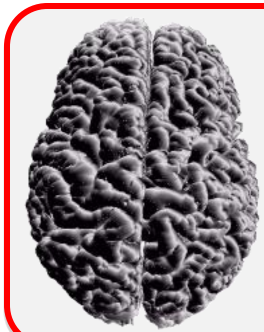
Virtual environment

HP

HRL LABORATORIES

CELEST

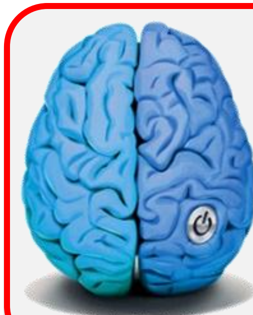
IBM



Human cortex

~10^6 neurons/cm^2
~10^{10} synapses/cm^2
~2 milliwatts/cm^2

vs.



Hardware goals

10^6 "neurons"/cm^2
10^{10} "synapses"/cm^2
~100 milliwatts/cm^2

The DARPA SyNAPSE project

Hardware goals

10^6 "neurons"/cm^2
10^{10} "synapses"/cm^2
~100 milliwatts/cm^2

10,000 chips, 1000 Watts stuffed in a shoebox

Microwave oven = 800 Watts

Dishwasher = 1500 Watts

~1000 Watts

Wrong hardware!

Stiff, nonlinear dynamical systems very **inefficient** in digital computers

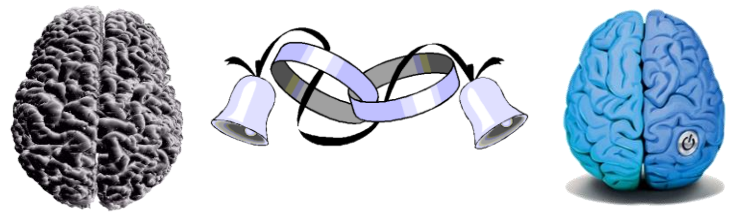
Brain
20 W
1.3Kg

10^{10} neurons
10^{14} synapses

Blue Gene
1 GW, thousands of racks

Happy Marriage

BOSTON UNIVERSITY



CELEST

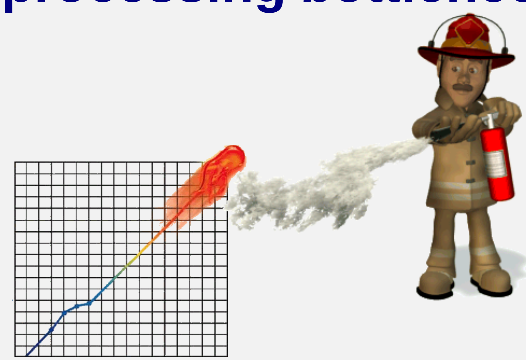
hp

Neuromorphic hardware

A brain-like hardware pushes modelers to face and solve tough constraints that brains face

local
low-power
robust
computation

Overcome key processing bottlenecks



Moore's law meltdown

The Team

Ennio Mingolla
Max Versace
Anatoli Gorchet
Heather Ames
Ben Chandler

New te

Jasmin Léveillé

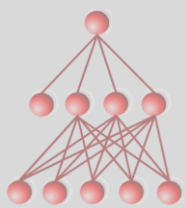
Gennady Livitz, s

Bridging the gap

Will not work…

von Neumann architecture

“Isolated” learning

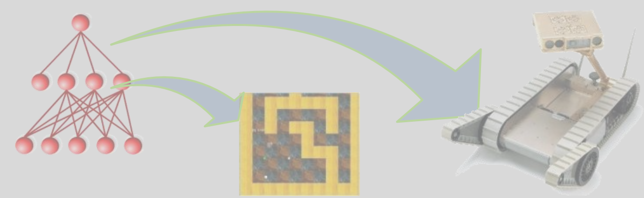


One man, one model

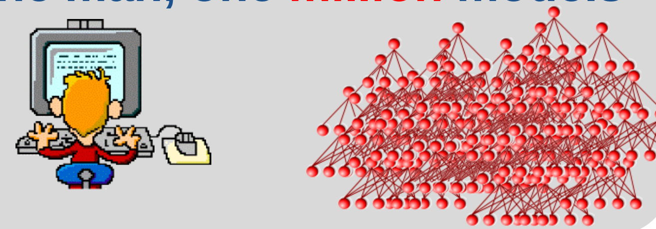
Maybe this will

Neuromorphic architecture

“Embedded” learning



One man, one million models



SyNAPSE projects for Phase I

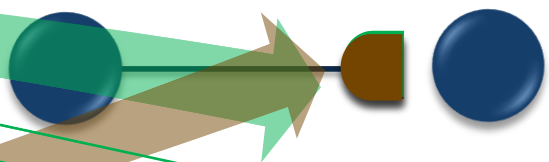
Learning — Analyze neural learning rules to inform chip design

Animat — Create an intelligent agent that can navigate a virtual environment and replicate rodent behavior

Infrastructure — Build a software framework to speed up modeling and parameter search

Learning Laws (L2)

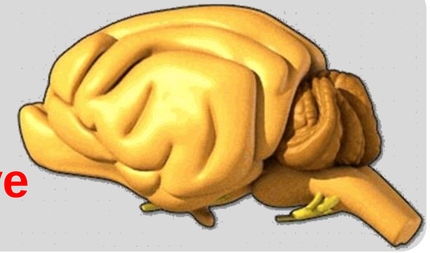
Family	Name	Equation	$f(y_j)$	$g(x_i,y_j)$	$h(x_i,y_j)$
Hebbian + decay flavors	Classic Hebb	$\dot{w}_{ij} = \lambda x_i y_j$	y_j	0	1
	Hebb + passive decay	$\dot{w}_{ij} = \lambda x_i y_j - \alpha w_{ij}$	y_j	α	1
	Pre-synaptic decay (outstar)	$\dot{w}_{ij} = \lambda x_i y_j - \alpha x_i w_{ij}$	y_j	αx_i	1
	Post-synaptic decay (instar)	$\dot{w}_{ij} = \lambda x_i y_j - \alpha y_j w_{ij}$	y_j	αy_j	1
	Oja	$\dot{w}_{ij} = \lambda x_i y_j - \alpha y_j^2 w_{ij}$	y_j	αy_j^2	1
	Dual OR	$\dot{w}_{ij} = \lambda x_i y_j - \alpha(x_i + y_j) w_{ij}$	y_j	$\alpha(x_i + y_j)$	1
	Dual AND	$\dot{w}_{ij} = \lambda x_i y_j - \alpha x_i y_j w_{ij}$	y_j	$\alpha x_i y_j$	1
Spiking	GVH	$\dot{w}_{ij} = \lambda(x_i y_j - w_{ij}) h(x_i y_j)$	y_j	1	vary*
Threshold Laws	Covariance 1	$\dot{w}_{ij} = \lambda x_i (y_j - \theta_{y_j})$ Where θ_{y_j} is a threshold: $\theta_{y_j} = \langle y_j \rangle$ †	$y_j - \theta_{y_j}$	0	1
	Covariance 2	$\dot{w}_{ij} = \lambda(x_i y_j - \theta_{x_i} y_j)$			
	BCM	$\dot{w}_{ij} = \lambda x_i y_j (y_j - \theta_{y_j})$ Where $\dot{\theta}_{y_j} = y_j^2 - \theta_{y_j}$ or $\dot{\theta}_{y_j} = \frac{y}{\alpha} - \theta_{y_j}$	$y_j(y_j - \theta_{y_j})$	0	1
	Original BCM (oBCM)	$\dot{w}_{ij} = \lambda x_i y_j \left(y_j - \theta_{y_j}\right) - \varepsilon w_{ij}$ Where $\dot{\theta}_{y_j} = \frac{y}{\alpha} - \theta_{y_j}$	$y_j(y_j - \theta_{y_j})$	ε	1



$$\dot{w}_{ij} = \lambda\left(x_i f(y_j) - g(x_i, y_j) w_{ij}\right) h(x_i, y_j)$$

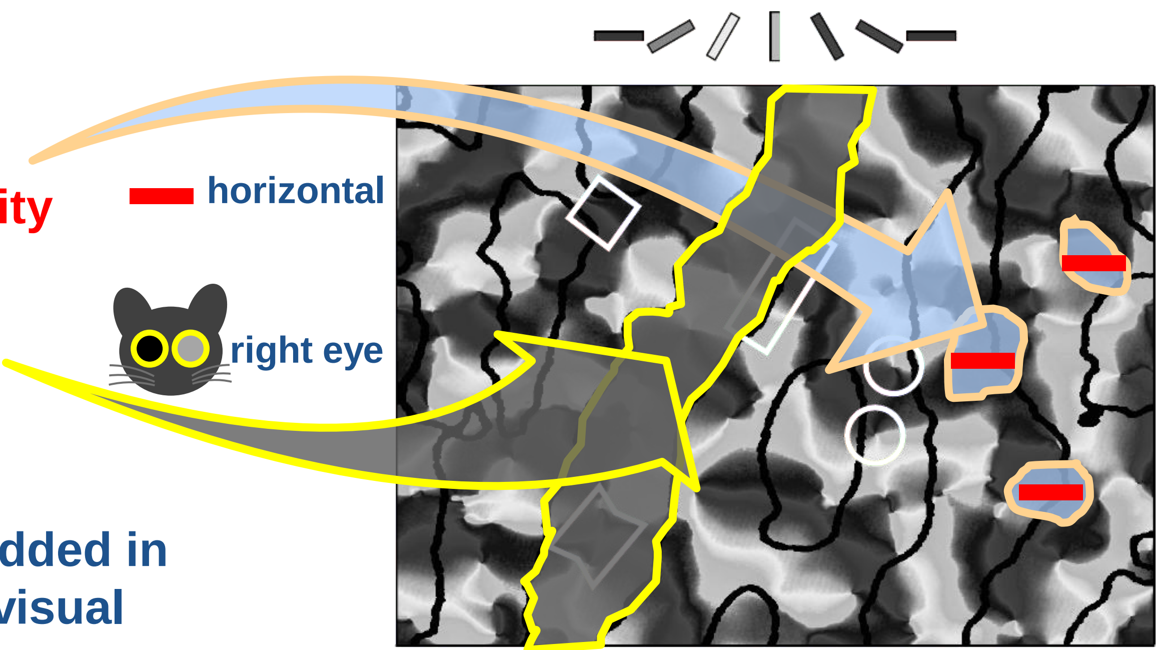
L2: Learning Laws

Cells in animal visual areas self-organize in early life to be selective for **orientation** and **input eye**



Spatially regular **orientation selectivity**

ocular dominance clusters



How do learning laws embedded in hardware **self-organize** the visual system compatible with

what is found in **biology** and

what is allowed by the **chip**

L2: Learning Laws

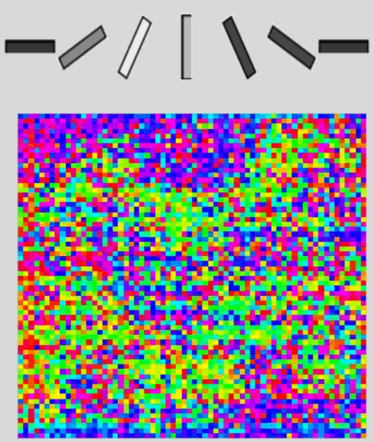
natural images

two eyes

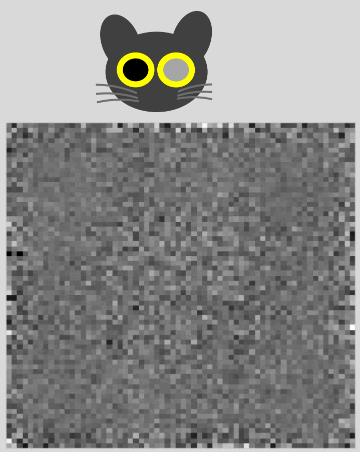
four thalamic populations

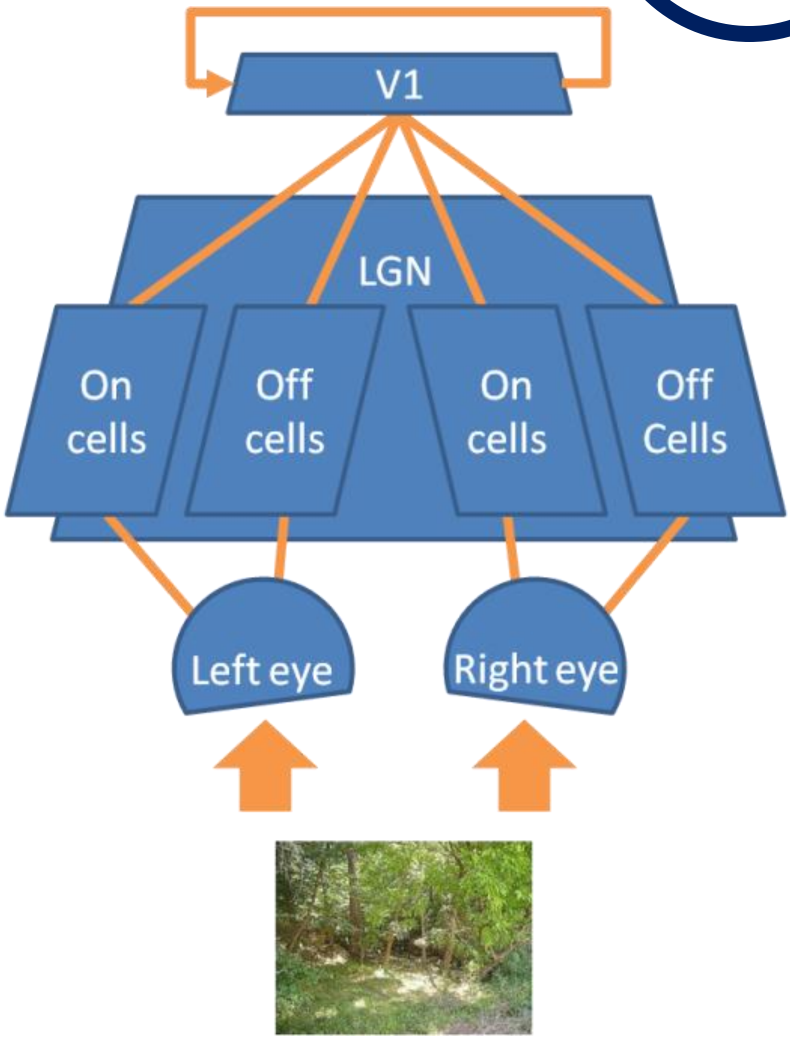
one visual cortical area

Orientation



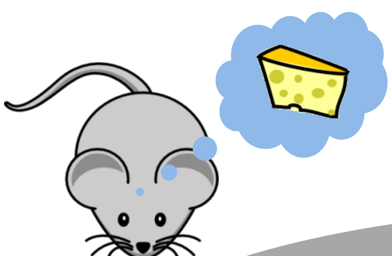
Ocular dominance

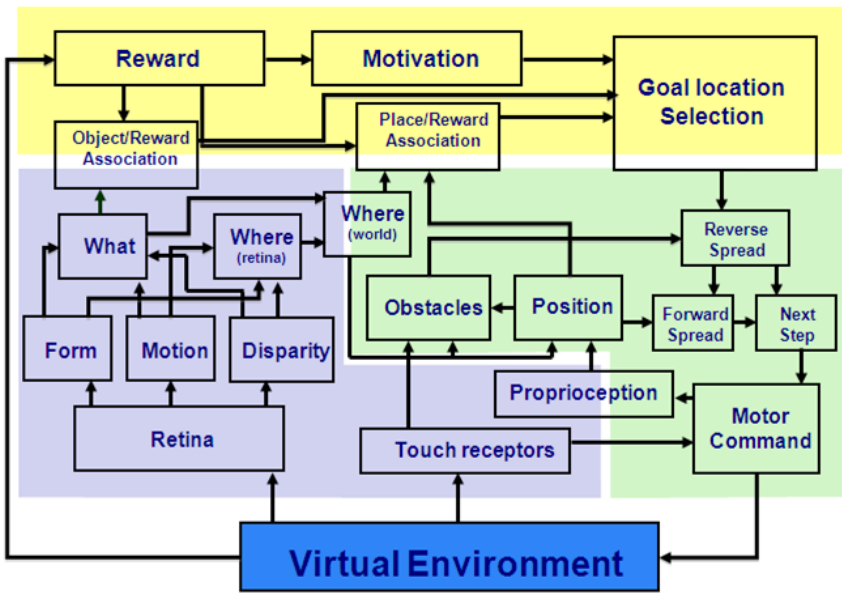


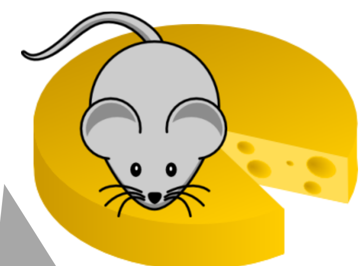


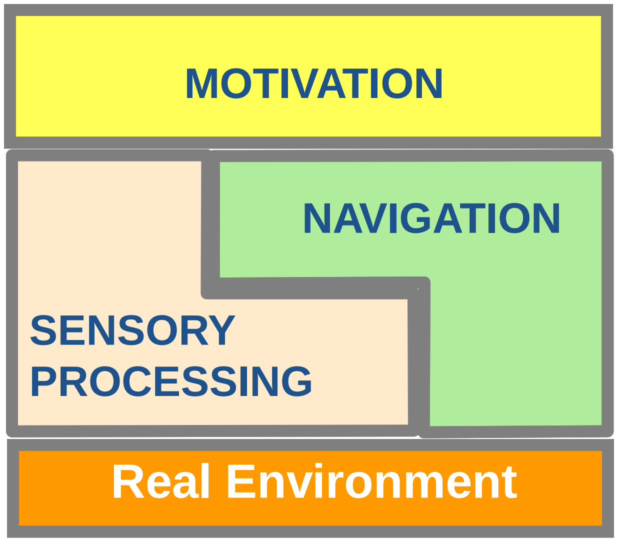
MoNETA

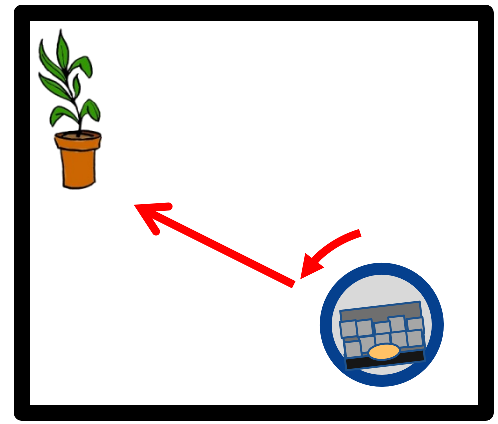
MOdular Neural Exploring Traveling Agent

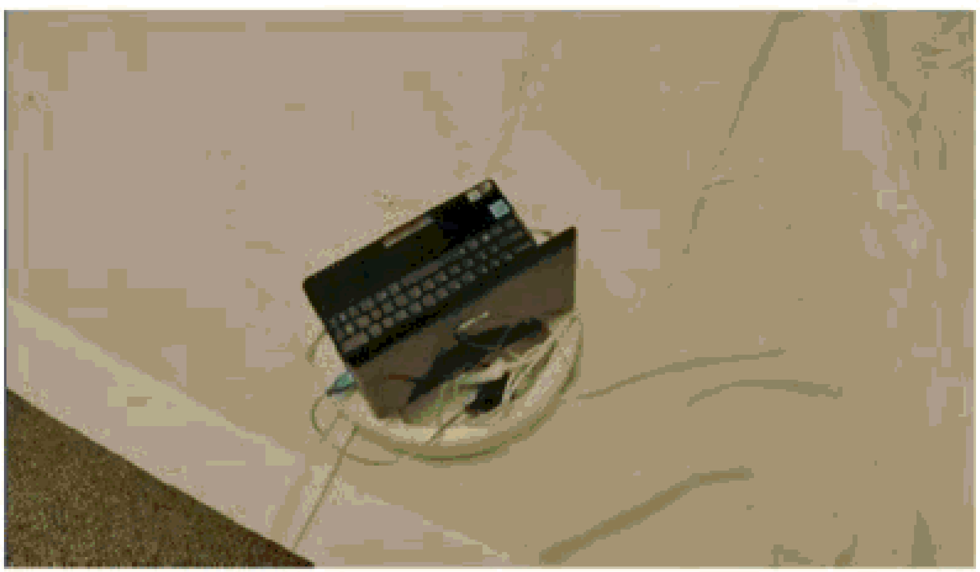







MOTIVATION
NAVIGATION
SENSORY
PROCESSING
Real Environment



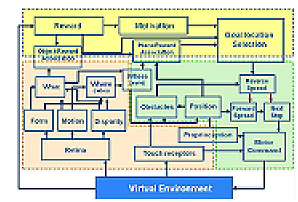


Educational spinoff: CN810

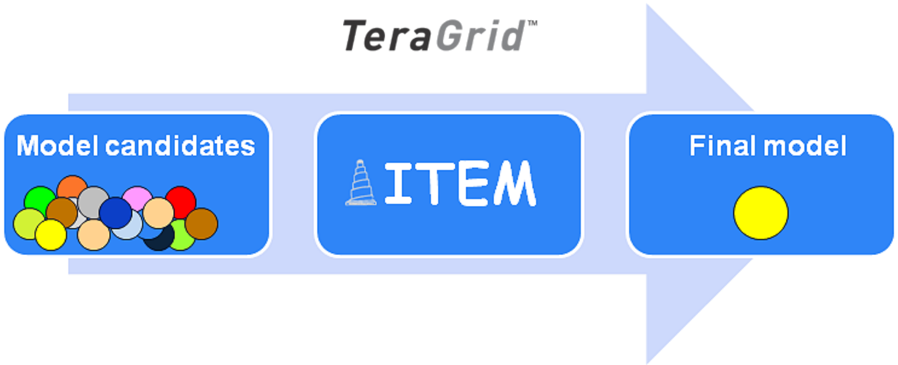
ItEM

ITerative Evolution of Models

How to build a brain?



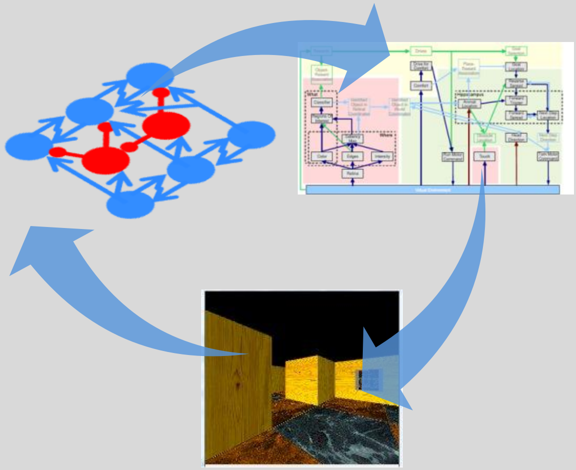
TeraGrid™



ItEM eliminates much of the manual effort required to explore the large space of possible model variations

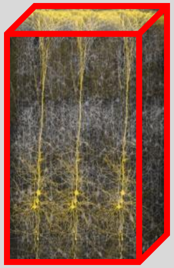
Quicker iteration on model design

Goal: function



Model whole brain system capable of intelligent behavior in increasingly complex environments

Subgoals: network



Dynamic stability of small networks

Canonical laminar cortical circuit able to stably **self-organize** its representation

Subgoals: whole brain system

Planning & execution

multiple goal representation,
sequencing,
adaptively timed behavior

QUESTIONS

Augmenting educational designs with social learning

Roy Pea

Stanford University, LIFE Center

Human Sciences & Technologies Advanced Research Institute
STANFORD UNIVERSITY

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Roots of translational research

- Vannevar Bush (1945)

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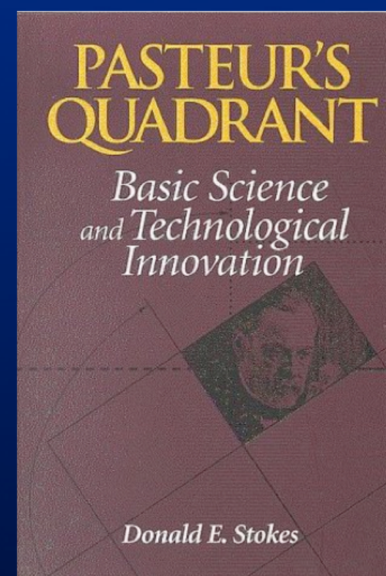
Roots of translational research

- Vannevar Bush (1945)

- Donald Stokes (1997)



Stokes (1997) Pasteur's Quadrant

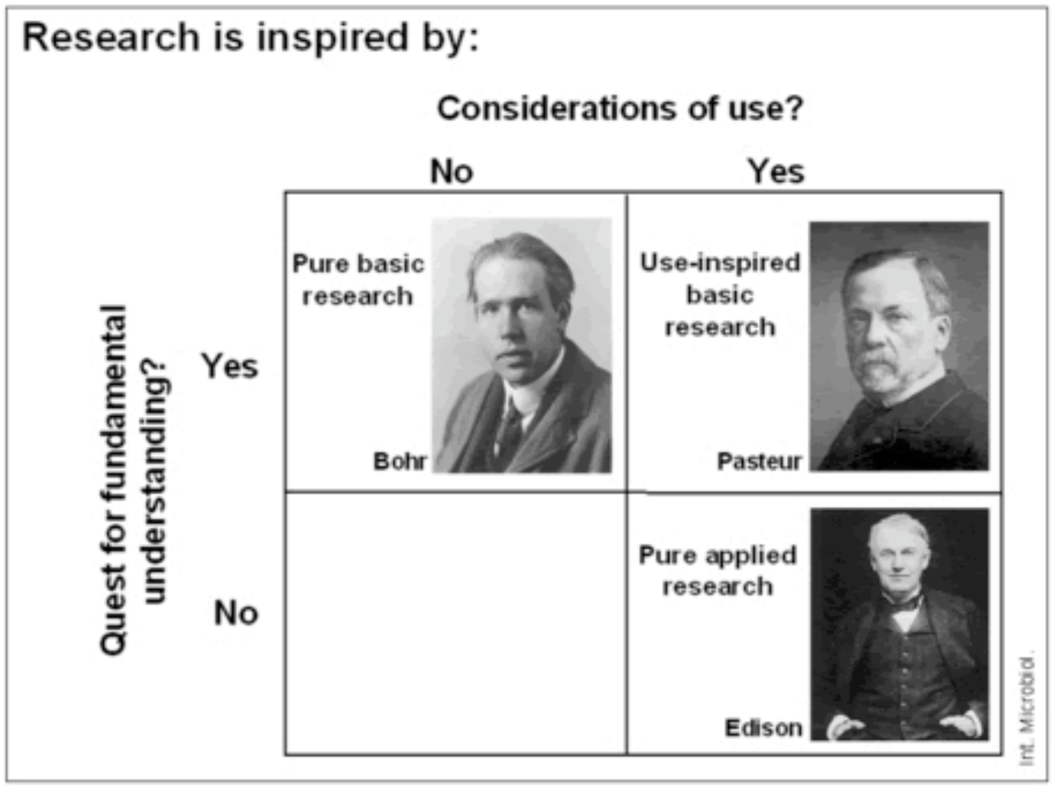


Fig. 3. Sources of research inspiration. Adapted from D.E. Stokes, *Pasteur's Quadrant* (1997).

Translational research in medicine

- NIH translational research: 60 Clinical and Translational Science Award (CTSA) centers funded by 2012 with $500Mil per year
- Translational research in medicine:
  - “effective translation of the new knowledge, mechanisms, and techniques generated by advances in basic science research into new approaches for prevention, diagnosis, and treatment of disease is essential for improving health" (Fontanarosa & DeAngelis, 2002, p. 1728).
- Yet also:
  - "improving access, reorganizing and coordinating systems of care, helping clinicians and patients to change behaviors and make more informed choices, providing reminders and point-of-care decision support tools, and strengthening the patient-clinician relationship" (Woolf, 2008).

Type-1 and Type-2 translational research

- Institute of Medicine's Clinical Research Roundtable
- T1:
  - "the transfer of new understandings of disease mechanisms gained in the laboratory into the development of new methods for diagnosis, therapy, and prevention and their first testing in humans. "
- T2:
  - "the translation of results from clinical studies into everyday clinical practice and health decision making."

Type I and Type II Matrix: Translational Research in the Learning Sciences

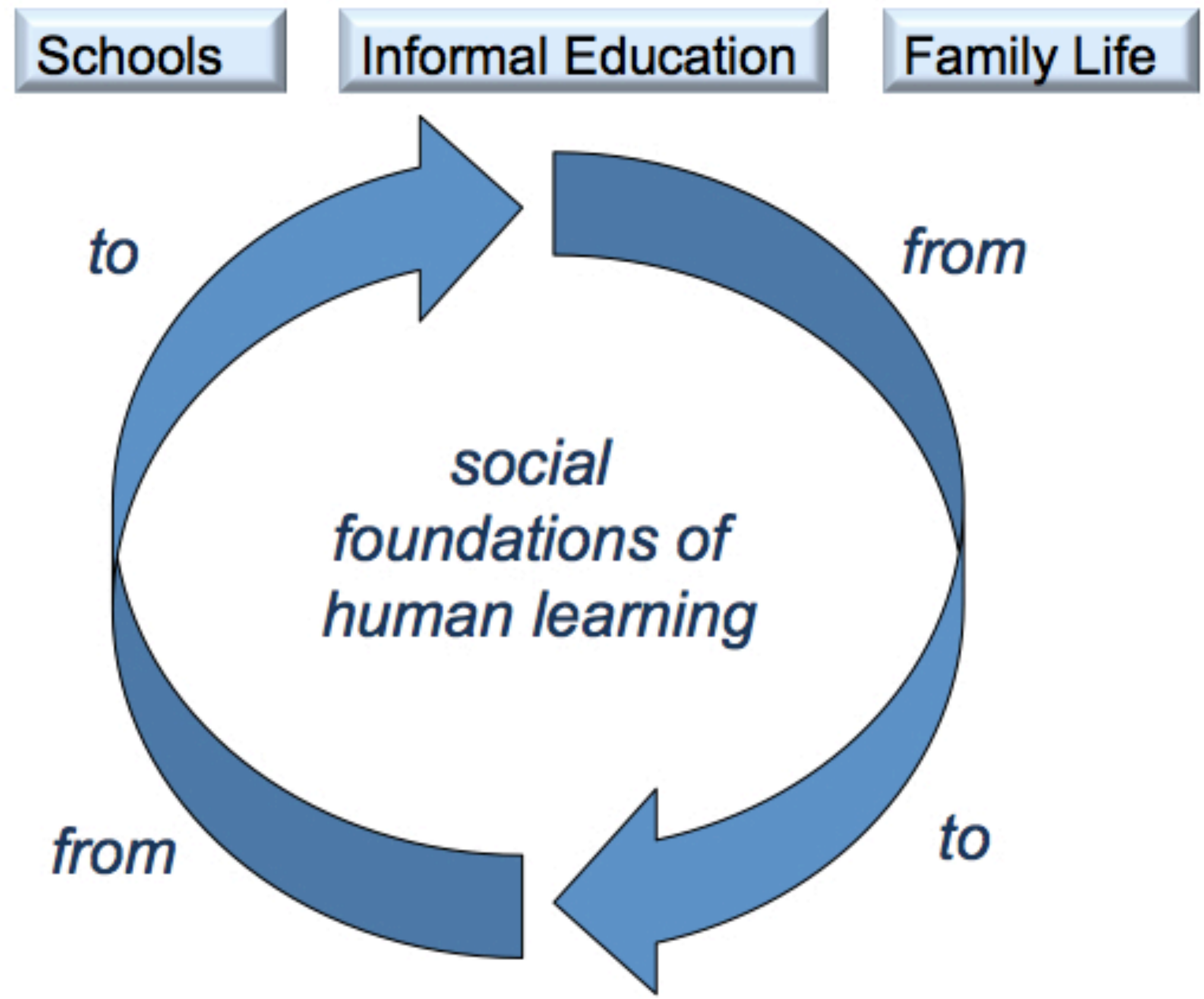
	Type I Translation	*Type II Translation*
What is being translated?	Translating principles from basic learning research into interventions	Translating interventions developed in one or a few settings into interventions that are scalable to many settings
What kind of research is involved?	Design-based research	Implementation research
What kinds of questions does translational research answer?	What do people learn from this design? How do people learn from this design? What do problems in learning or implementation suggest about re-design of the intervention?	What kinds of capacities are required for organizations to implement this design? What supports are needed for people implementing the design to adapt it in ways aligned with the core principles of the design?
Who is involved?	Learning scientists, classroom teachers, subject matter experts, often also software developers	Learning scientists, organizational researchers, teacher leaders, school and district administrators, also often publishers

Four features of translational research in the learning sciences

1. Intentional stance
2. Guided by *descriptive* analysis of systemic factors contributing to human practice dynamics
3. Embodying a *prescriptive theory of action* for how translational research will leverage the systemic factors hypothesized to contribute most to enabling the human practices to change
4. *Reciprocal influences* of science and practice improvements

LIFE Translational Research

Learning Designs



Lab & Field

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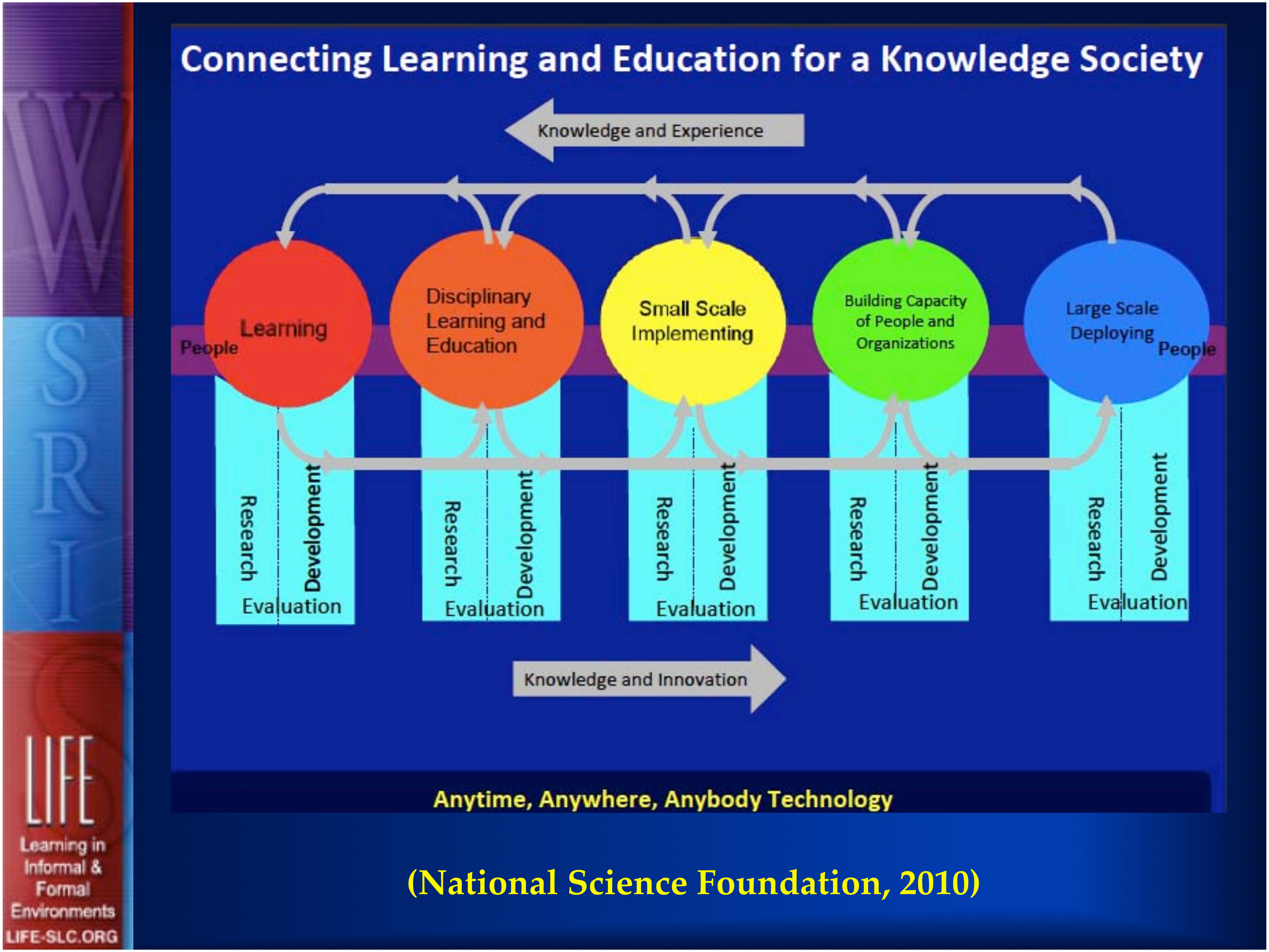

(National Science Foundation, 2010)

Special challenges of translational research for LIFE social learning focus

- *LIFE purpose:* To develop and test principles about the social foundations of human learning in informal and formal environments with the goal of enhancing human learning from infancy to adulthood
- The systemic factors that contribute to human practice dynamics are very different for:
  - Family/home settings (informal learning, typically)
  - Community or after-school settings/programs (informal education)
  - School and workplace training settings (formal education)

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"Arcs of work" – LIFE Translational Research

1) Making curricula more socially responsive
2) Leveraging "the mere belief in social" for technology-enhanced STEM learning
3) Social role playing for improving Advanced Placement courses
4) Brain measures linked to socio-cultural context of bilingual language acquisition
5) Social robotic language teaching aids in the preschool
6) Using social learning and gaming principles to encourage energy conservation
7) From 'co-viewing media' to 'joint media engagement' for science learning

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Leveraging Student Interest and Choice in Designs for STEM Learning in Formal and Informal Contexts

William R. Penuel
SRI International

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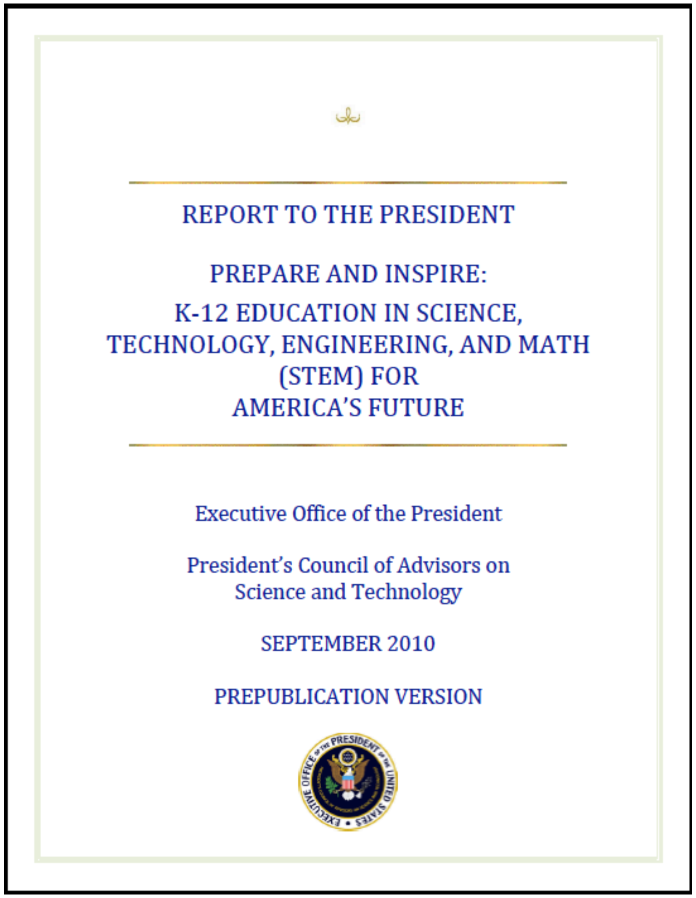
LIFE Researchers Involved

- **Philip Bell,** University of Washington, Seattle
- **John Bransford,** University of Washington, Seattle
- **Nancy Vye,** University of Washington, Seattle
- **Carrie Tzou,** University of Washington, Bothel
- **Giovanna Scalone,** University of Washington, Seattle
- **Kari Shutt,** University of Washington, Seattle
- **Katie Van Horne,** University of Washington, Seattle
- **Tiffany Lee,** University of Washington, Seattle
- **Kieran O'Mahony,** University of Washington, Seattle
- **Rachel Phillips,** University of Washington, Seattle
- **Christopher Harris,** SRI International
- **Britte Haugan Cheng,** SRI International
- **William R. Penuel,** SRI International

The Need for Innovation in STEM Education



REPORT TO THE PRESIDENT

PREPARE AND INSPIRE:
K-12 EDUCATION IN SCIENCE, TECHNOLOGY, ENGINEERING, AND MATH (STEM) FOR AMERICA'S FUTURE

Executive Office of the President

President's Council of Advisors on Science and Technology

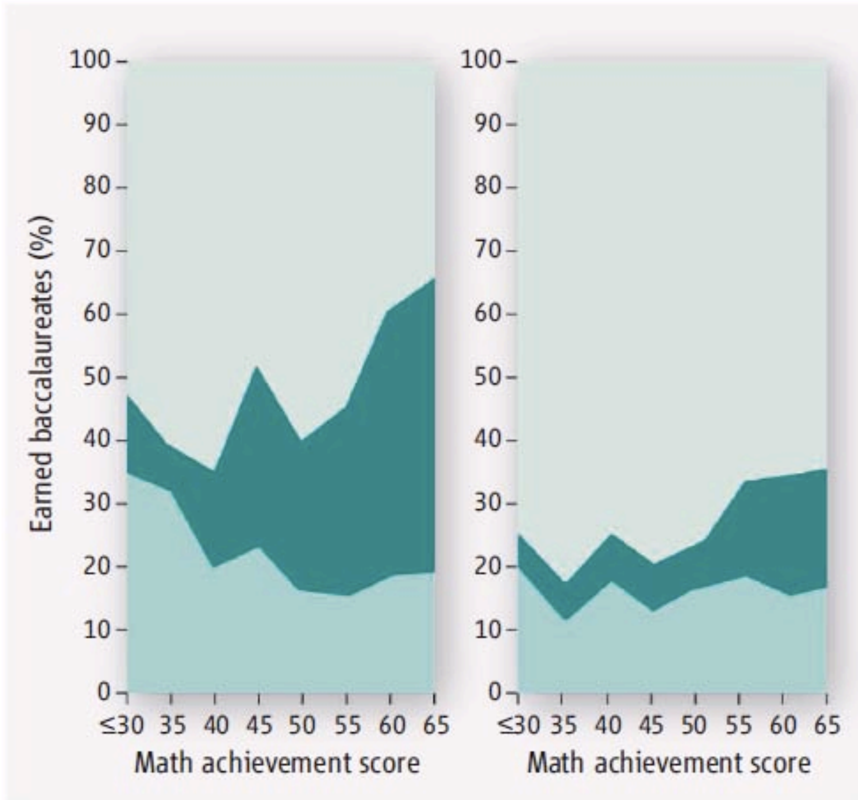
SEPTEMBER 2010

PREPUBLICATION VERSION

RECOMMENDATION 5: CREATE OPPORTUNITIES FOR INSPIRATION THROUGH INDIVIDUAL AND GROUP EXPERIENCES OUTSIDE THE CLASSROOM

STEM education is most successful when students develop personal connections with the ideas and excitement of STEM fields. This can occur not only in the classroom but also through individualized and group experiences outside the classroom and through advanced courses.

Choosing and Valuing: Linked Social Processes in Learning



Proportion of earned baccalaureates. Degrees in life science (light green), physical science/engineering (dark green), and nonscience fields (gray). Students who in eighth grade expected a science degree are shown on the left (n = 337); those who did not expect a science degree are shown on the right (n = 3022).

Source: Tai, R. H., Liu, C. Q., Maltese, A. V., & Fan, X. (2006). Planning early for careers in science. *Science, 312,* 1143-1144.

Foundations of Interest in Early Childhood

- Children are "born investigators" (National Research Council, 2010)
- Parents can and do extend children's emerging interests in science expressed in everyday settings by providing brief explanations of phenomena they encounter in places like museums (e.g., Crowley & Galco, 2001) and reflecting on experiences afterwards in other settings (Bell et al., 2006)
- To date, much intervention research focused on interest development focuses on out-of-school science (Bell, Lewenstein, Shouse, & Feder, 2009)



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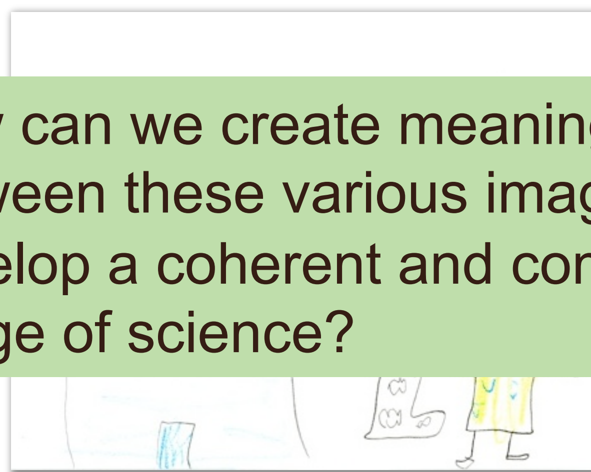
LIFE Study of Kindergartners' Images of Science (Lee, 2010)

- Research Question: *What are beginning kindergarten scientists' images of science?*
- Participants (*n* = 33)
  - 17 females, 16 males
  - Students come from an elementary school consisting of 72 percent Caucasian, 16% Asian, and 10% multi-ethnic students
  - Data collected within students' first two months of school
  - Curriculum in use: Full Option Science System
- Methods
  - Draw a Scientist Test (Chambers, 1983)
  - Interviews with students related to conceptions of science

LIFE Study of Kindergartners' Images of Science (Lee, 2010)

- These young children entered school able to identify science-related activities and were aware of some scientific terms like "experiment" and "chemistry
- Children's developing conceptions of science were varied but would be considered by adults to be relevant to science (e.g., chemistry labs, science museums, school science experiments)
- Students' reported out-of-school science experiences and interests did not align with school science activities

Media-Influenced



Everyday

School

How can we create meaningful connections between these various images of science to develop a coherent and comprehensive image of science?

Redesigning Widely-Used Inquiry Science Kits

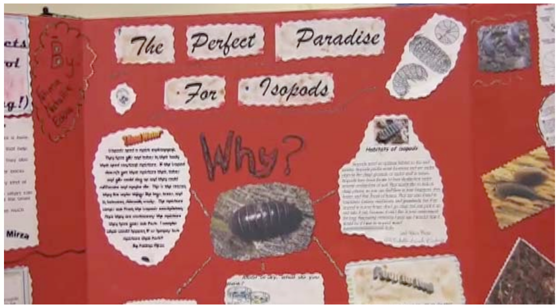
- FOSS and other "inquiry kits" used in the kindergarten study have been adopted by many US schools and districts
- Two linked efforts focus on leveraging findings about *choice, agency,* and *positioning* to inform the redesign of kits to enhance interest and learning
  - Ethnographic studies in LIFE highlight how the fields of *choice* experienced by learners substantially shape their learning in informal environments
  - Also, in *agentive* ways, children often self-select learning topics and how they choose to learn, including with whom
  - *Positioning* (Harré, 2008), acts of defining and maintaining clusters of rights and duties associated with performing certain actions strongly shape the field of choices individuals can pursue

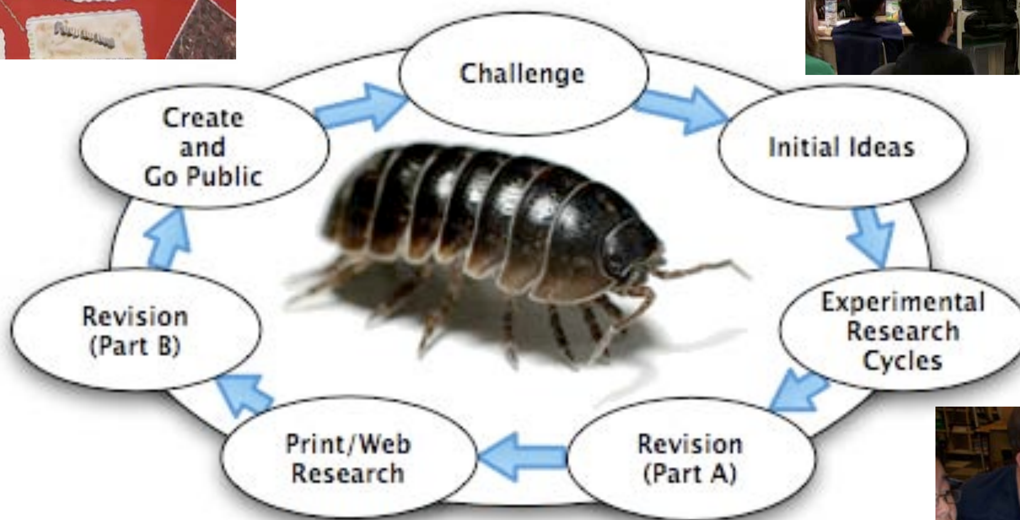
Redesigning Widely-Used Inquiry Science Kits

	Isopod Habitat Challenge Team	Micros and Me Team
Critique of Existing Kits	Topic-based Episodic inquiry No revision Teacher-directed	Presumed relevance Not consequential Presumed to be acultural, but not inclusive
Focus of Redesign	Challenge-based Sustained inquiry Feedback/revision *Student choice/agency*	Personally consequential Culturally responsive to community practices *Investigations centered on student interests*

Learning in Informal & Formal Environments
LIFE-SLC.ORG

Isopod Habitat Challenge





Learning in Informal & Formal Environments
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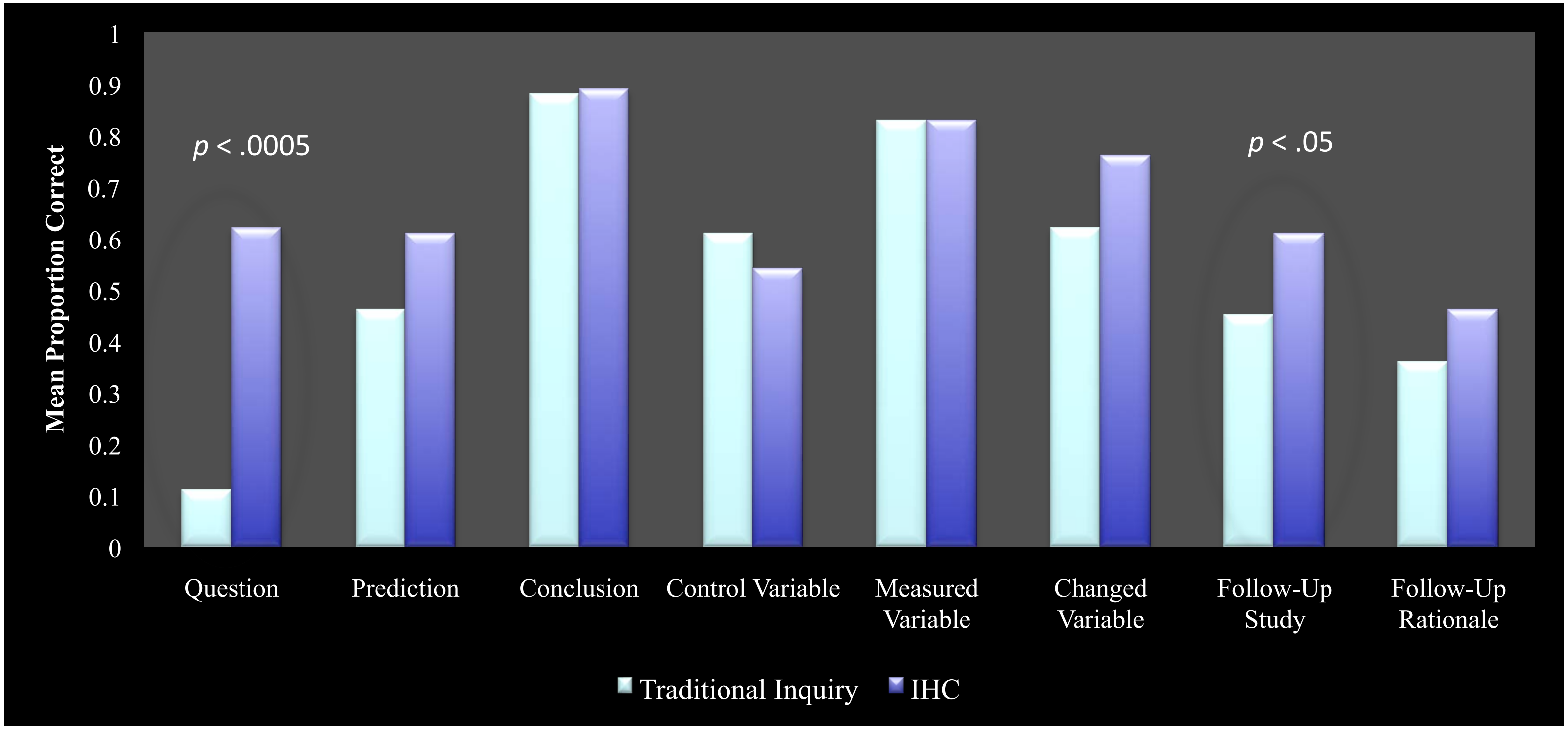
Isopod Habitat Challenge Study

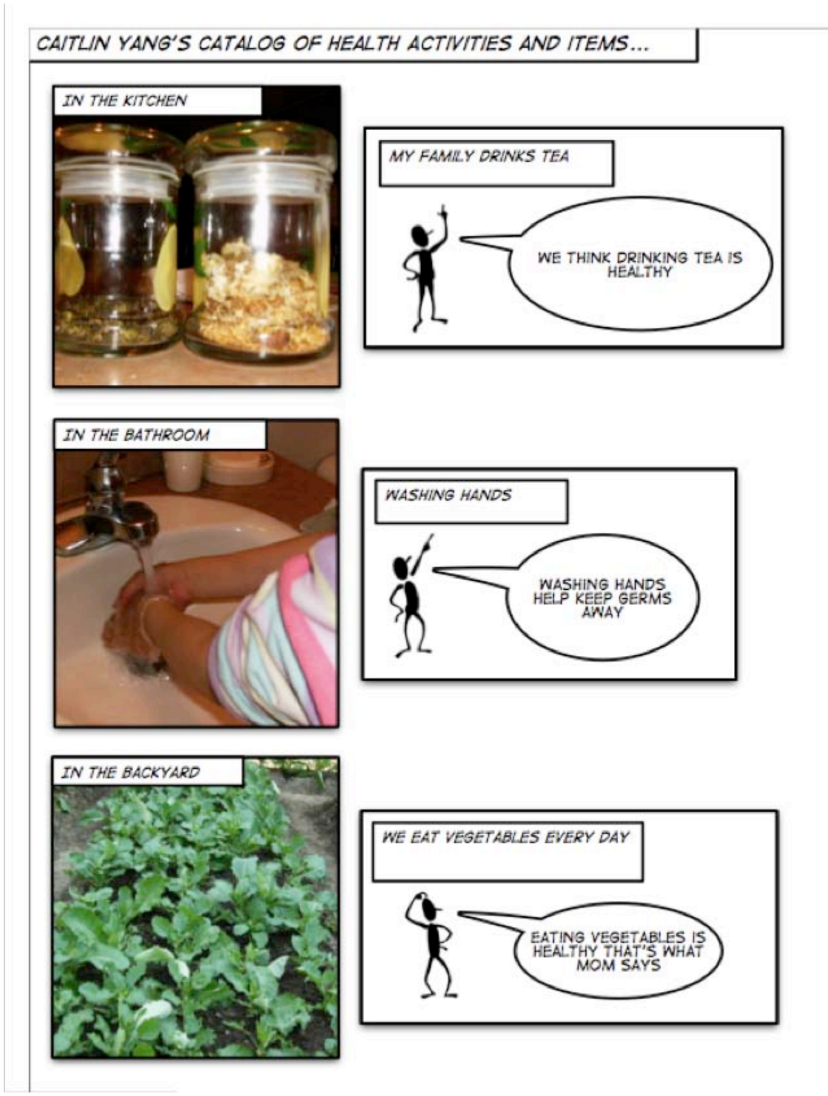
- Research Question: *How can findings from informal learning arrangements that highlight student choice and agency affect school programs for enhancing self-directed science inquiry?*
- Participants
  - 13 5th grade teachers in a single district
  - Schools were randomly assigned a treatment or comparison condition (multiple teachers in one school; comparison teachers implemented the traditional kit
  - 7 teachers, 122 students in treatment (IHC) group, 6 teachers, 72 students in comparison classrooms
- Methods
  - Used district content assessment that combined multiple-choice and short answer questions
  - Embedded inquiry assessment

Isopod Habitat Challenge Study



- No differences on district-developed content assessment
- Students in the IHC classrooms had significantly higher rubric scores than students in comparison classrooms for the quality of their question posing and designs for a follow-up study to their investigations

Micros and Me: Surfacing cultural health practices through self-documentation



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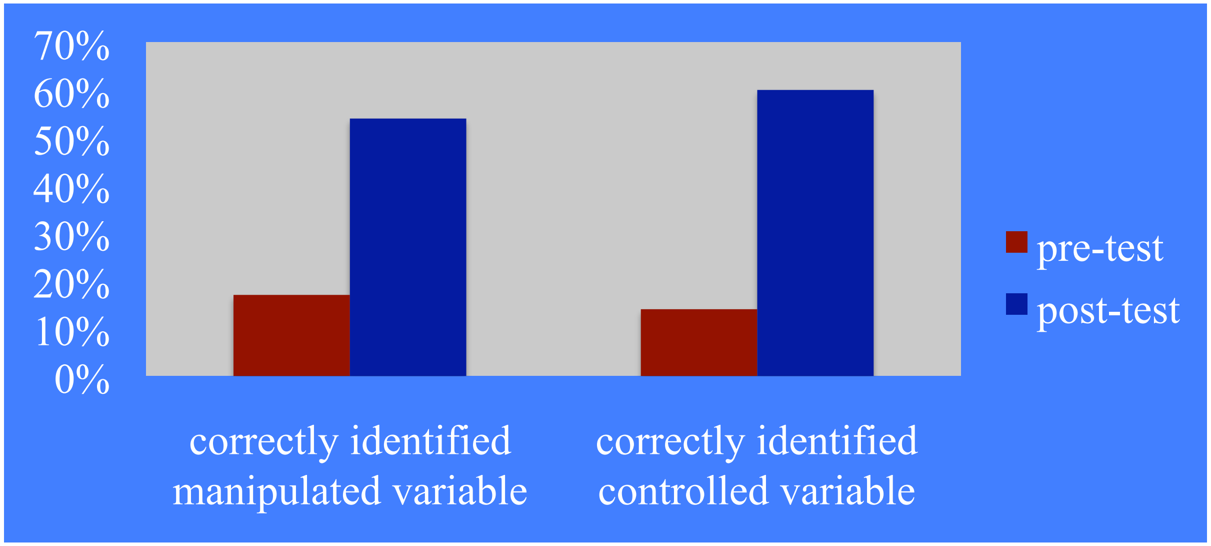
Micros and Me Study

- Research Question: *How can we leverage youths' repertoires of practice in the redesign of commercially-available inquiry science kits*
- Participants
  - Design-based research (iterative cycles of revision)
  - Single-group, pretest-postest design for analysis of outcomes (second iteration)
  - Granite Elementary School: 63% Free or Reduced Price Lunch, 40% ESL, significant cultural and linguistic diversity (e.g., 5% Caucasian students), large percentage of students from first generation immigrant families
- Methods
  - Analyses of video recordings of classroom interactions
  - Analyses of students' self-documentation artifacts
  - Co-design teachers' reflections in interviews on their learning

Micros and Me Study



- Compared with their scores on the researcher-developed assessment, students' posttests were significantly higher for identifying manipulated and controlled variable in an experiment
- Teacher (does this mean it's just one class of results) reported all parents mentioned during parent-teacher conferences how science curriculum topics were a focus of discussion at home and were shaping children's everyday actions
- Teachers incorporated strategies of culturally responsive instruction into other grade levels and units; gained more complex notions of community and culture; put a priority on connecting science to students' cultural lives

Type I Translation Research

- Team comprised of researchers from SRI and a graduate student from UW conducted *implementation research* on both units
- Research Question: *How do teachers implement the curricula in the classroom?*
- Methods
  - Varied by project, given time of entry into involvement
  - *IHC:* Classroom observations using both structured protocols and ethnographic fieldnotes, teacher interviews
  - *Micros and Me:* Analysis of discourse from video recordings of teachers

Type I Translation Research

- There is evidence from both redesigns that the new curriculum materials help teachers elicit student thinking and experiences
- Variability that makes a difference in terms of consequences for how classroom learning unfolds has to do with classroom *uptake* of student contributions
  - In IHC classrooms, variability in teachers' engaging in moves to help develop students' questions mattered most
  - In Micros and Me classrooms, variability in uptake of the meanings of "cultural" with respect to practices mattered most
- Primary implications of this Type I translation research: Identification of additional teacher learning supports

Synergistic New Funding

- NSF DRK-12 grant: Exploring social learning principles in the context of curriculum redesign (Bransford, Vye, Bell, Shouse)
- US Department of Education i3 grants:
  - Explore STEM project-based instruction throughout a high school (Shouse, Bell)
  - Promote arts-based school improvement efforts across a district (Bransford, Vye)
- NSF Ocean Science Education Center: Renewed COSEE center will develop and study citizen science educational programs for minority youth (Bell, Tzou)

Emerging Directions: Innovations that Span Multiple Settings

Tribal leader Monica Charles talking with children about their role in habitat restoration

Models of Translation Research

Daniel Schwartz

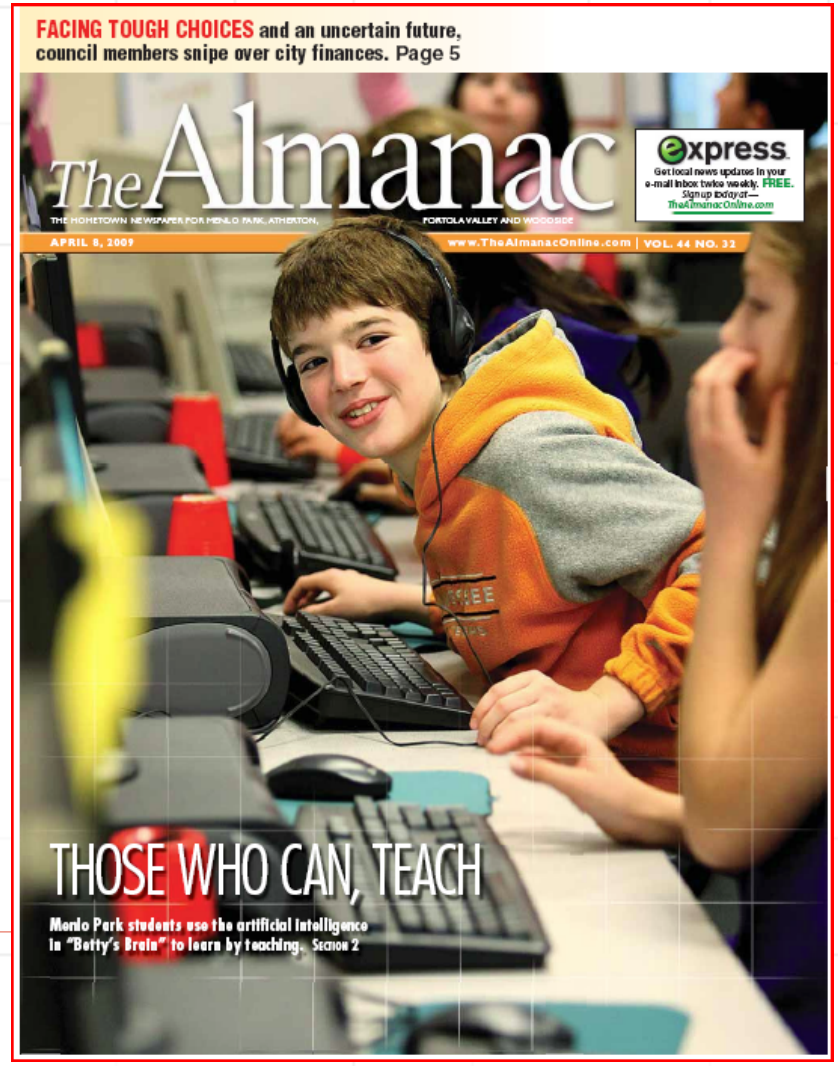
LIFE Center

AAA lab @Stanford

Not a translation theorist

- But, even I know you have to show pictures of happy recipients in education!

A Teachable Agent



FACING TOUGH CHOICES and an uncertain future, council members snipe over city finances. Page 5

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THOSE WHO CAN, TEACH

Menlo Park students use the artificial intelligence in "Betty's Brain" to learn by teaching. SECTION 2

My Naïve Model of Translation

- In many cases, it involves a chain of hand-offs among people with different expertise.
- Scientist → Engineer → Designer → User
- User → Designer → Engineer → Scientist

Centers are unique

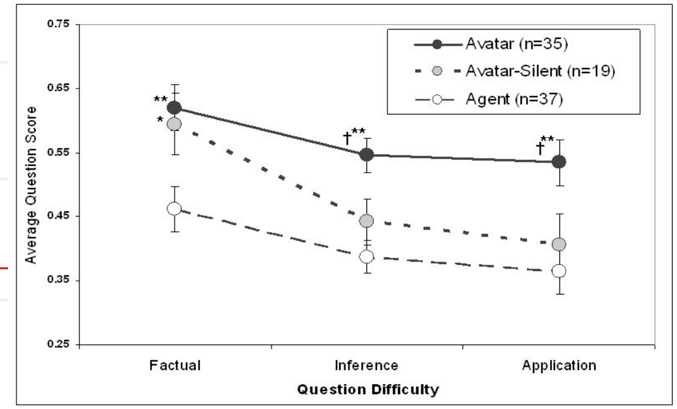
- Given LIFE, the same people are often involved at all points of the chain.
- Insider vantage might provide some insight on different types of translation.
- In this example, we are translating basic research on "social facilitation."

“Basic Science” Examples

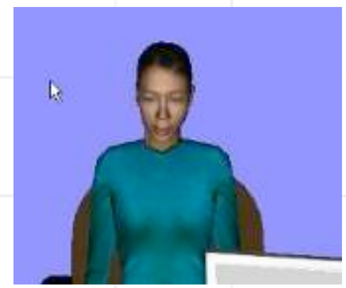
Sandra Okita
Columbia

Social Beliefs and Complex Learning

- Told character was a person or computer.
- Learning science content. <u>Identical interactions</u>.
- More learning/arousal/attention in social
- Arousal predicts learning
- Social “Interaction” is key



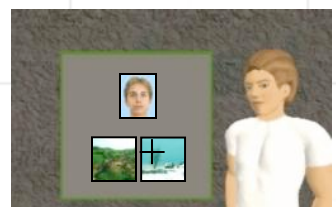
Greater than Agent condition: * p < .05, ** p < .01
Greater than Avatar-Silent; † p < .05

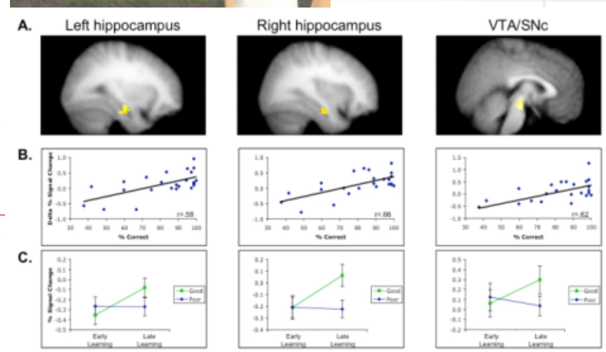


Janice Chen
Stanford

Evidence on the Neural Basis

- Learning associations
- Arousal predicts learning again
- Hippocampus, amygdala, reward/feedback circuitry implicated



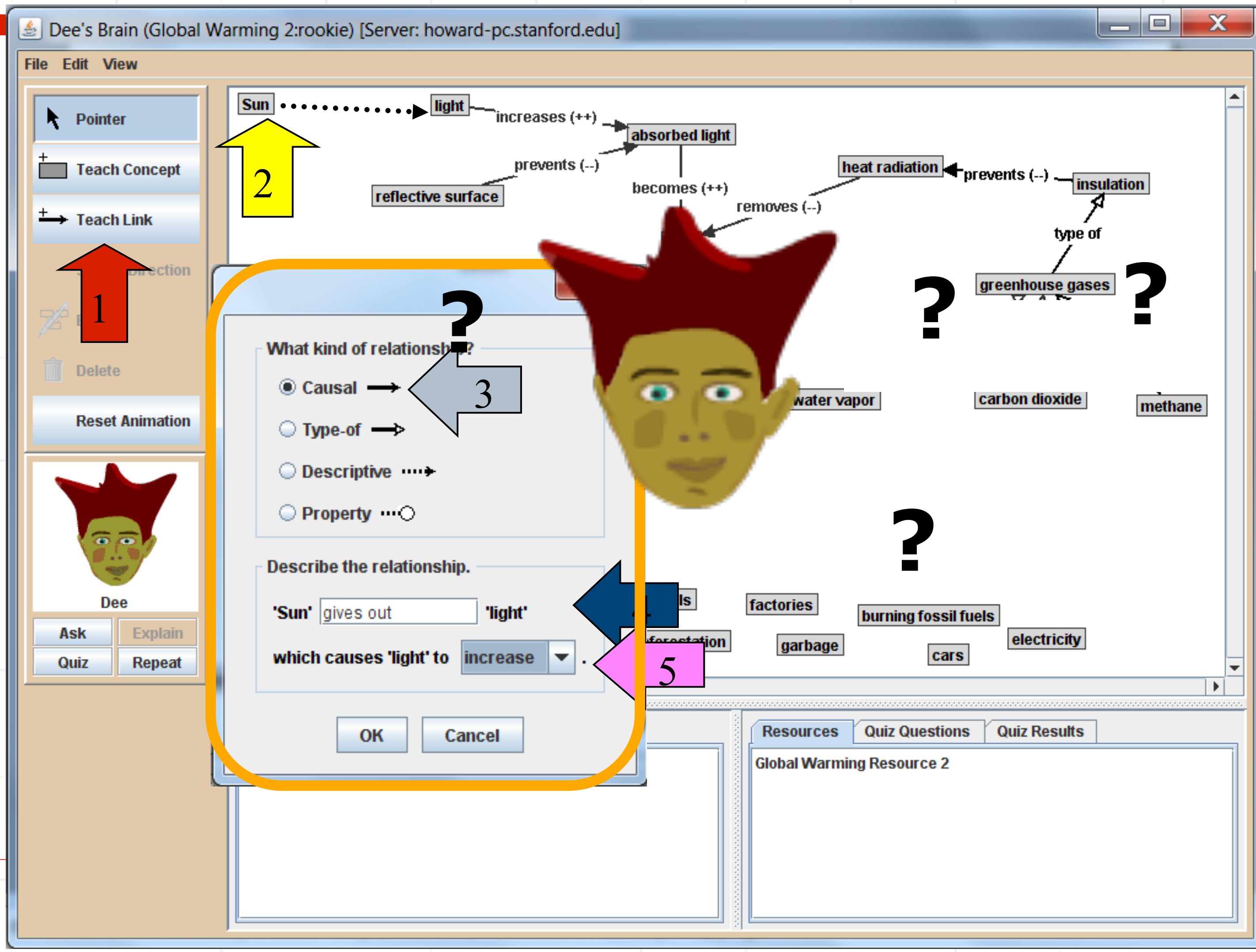


Focus on One Instance of Translation: Teachable Agents (TA)

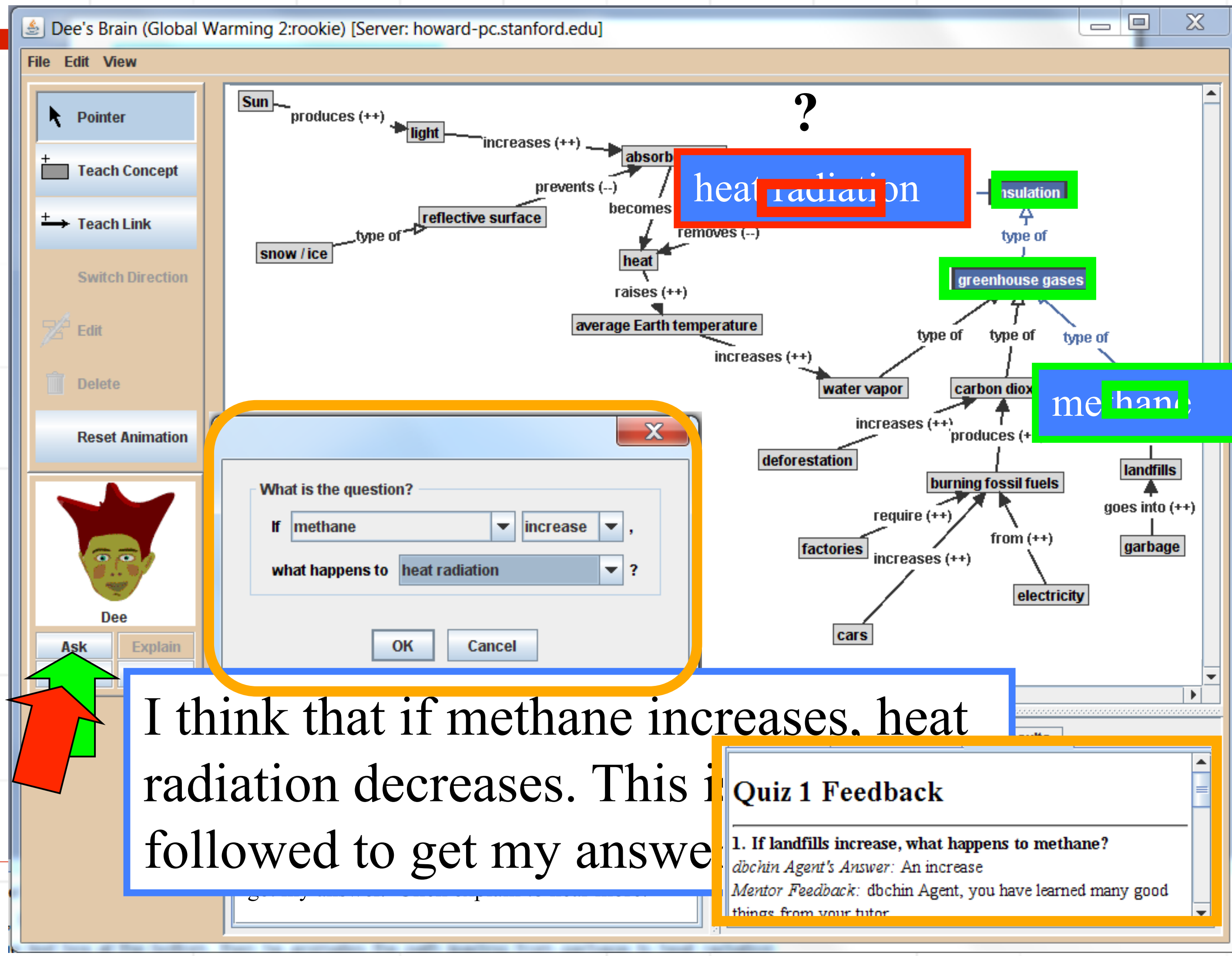
Gautam Biswas (Vanderbilt)

Students learn by ***adopting*** and ***teaching*** a computer agent.

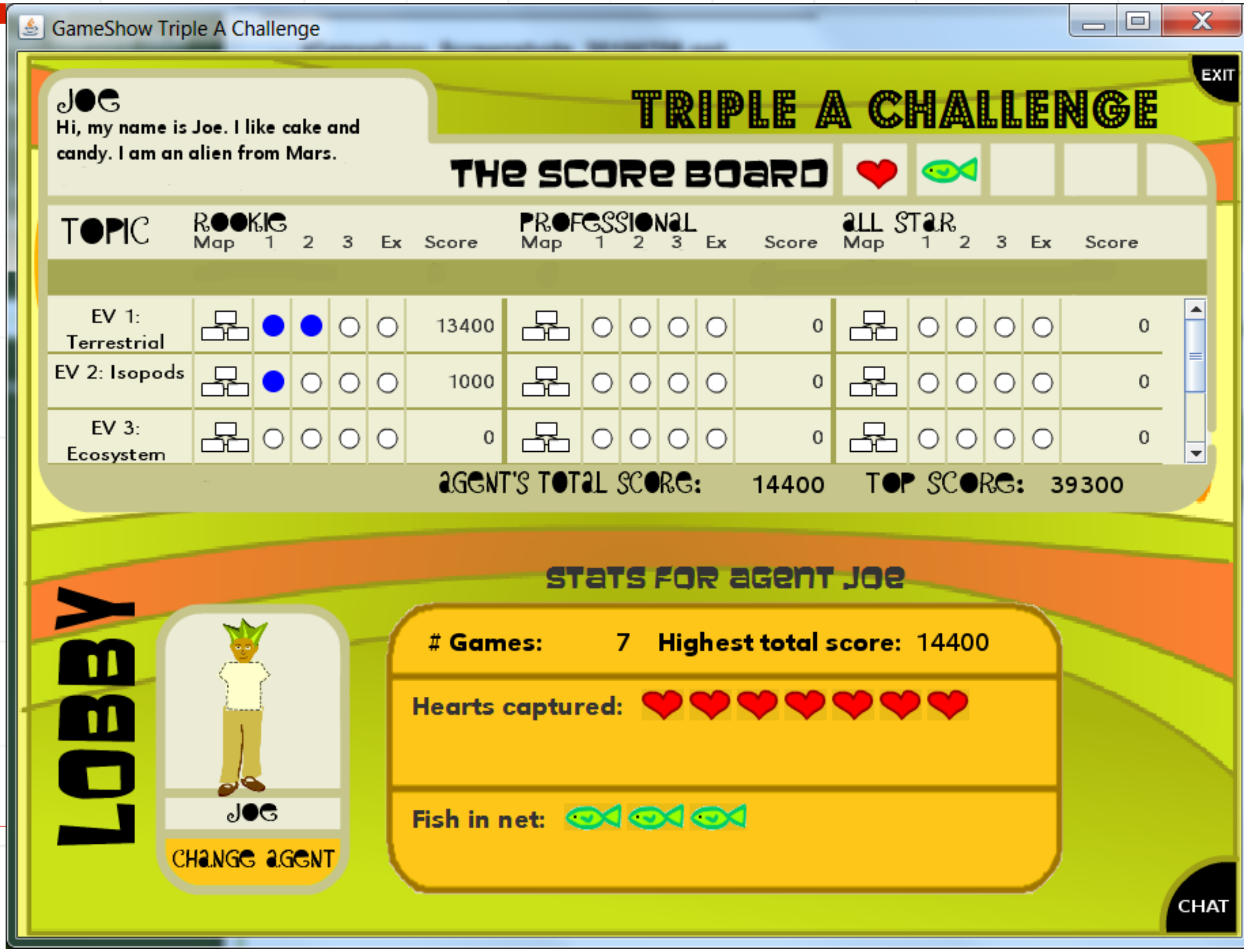
Teaching Your Agent



Understanding Your TA



Larger Environment



Gameshow Used for Homework

Host asks questions

Your agent answers.

You wager on how you think your agent will do.

Different Models of Translating with Teachable Agents

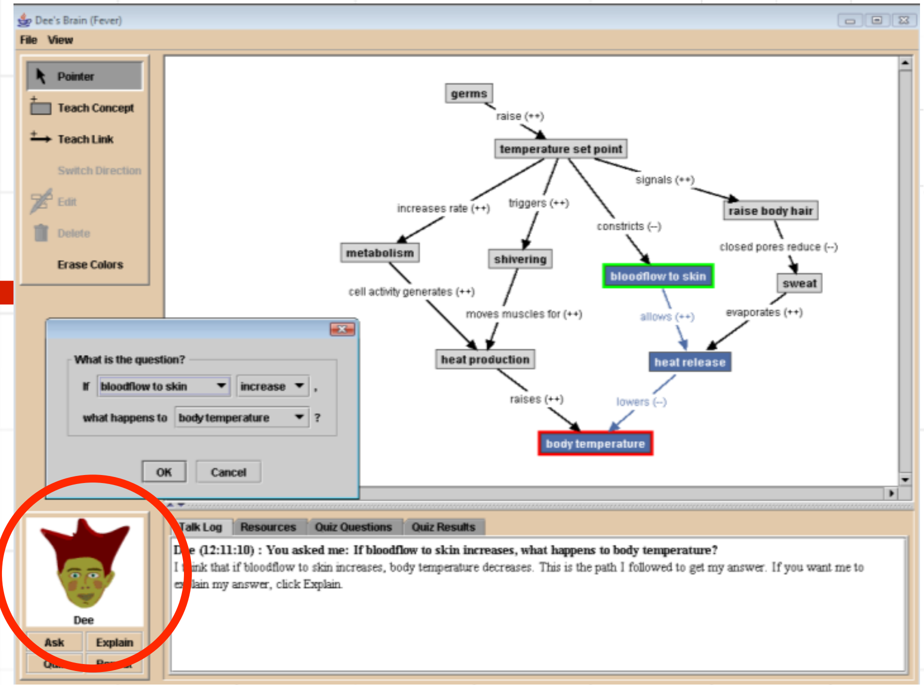
- Translation Research
  - Science of Context
  - Specifying Effects
  - Iterative Refinement

Basic Science on Context

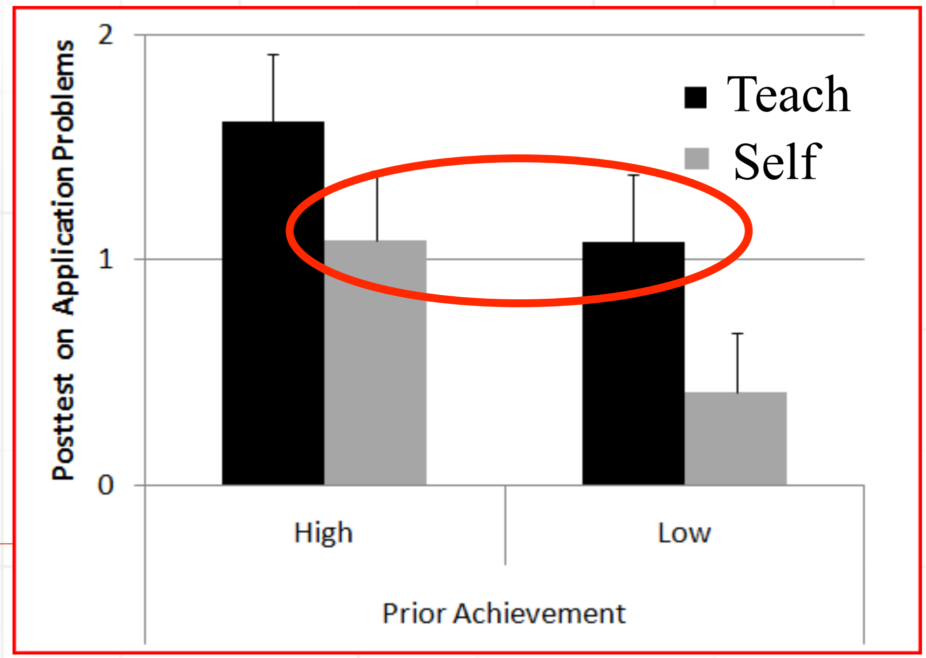
- Many of the SLC's focus on the internal world of the mind and brain.
  - Context is a way to probe the internal states.
  - Translation as a process of extending science findings thru increasingly complex contexts.
- LIFE studies learning contexts ***per se***.
  - It counts as part of our basic science portfolio.
  - In this model, translation research is basic research.

Science of Context

Cathy Chase
Stanford



- Teach agent v. self.
  - 50 8th-graders.
  - The context of beliefs
  - "Mere belief" manipulation.
- Teach condition learns better.
  - Low achiever boost.
  - Follow-up research on why.
- Students work harder to learn for their agent than themself.
  - Double the amount of time reading!



Different Models of Translating with Teachable Agents

Translation Research

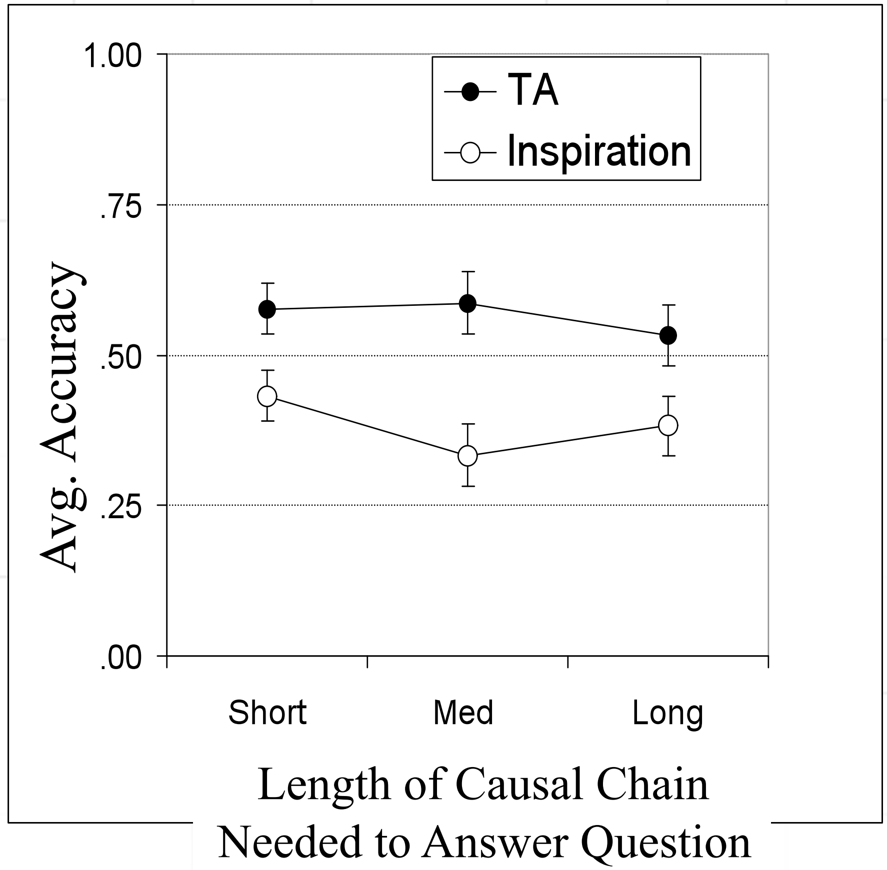
- Science of Context
- Specifying Effects
- Iterative Refinement

Specifying Effects of the Translation

- Are the effects positive by standards of the stakeholders?
  - Precise learning outcomes.
  - Better than current standard?

Comparative Study to Identify Precise Effects (~60 5th-graders)

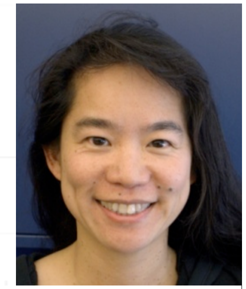
- Kids made maps using Teachable Agent versus *Inspiration*
  - Inspiration is a concept mapping tool used in very many schools.
- Topic: Global warming
  - 27 nodes, 31 links, 3 feedback loops
- TA advantage specific to causal reasoning.



Specification of Effects

- Are the effects positive by standards of the stakeholders?
  - Precise learning outcomes.
  - Better than current standard?
  - Side effects?
  - Lasting effects?
- Bigger samples become important when looking for side effects and generalization.

Do Teachable Agents provide added value without side effects?



Doris Chin
Stanford

~150 Children and 6 Teachers
6th-grade science

All teachers used the same science kits. (FOSS).

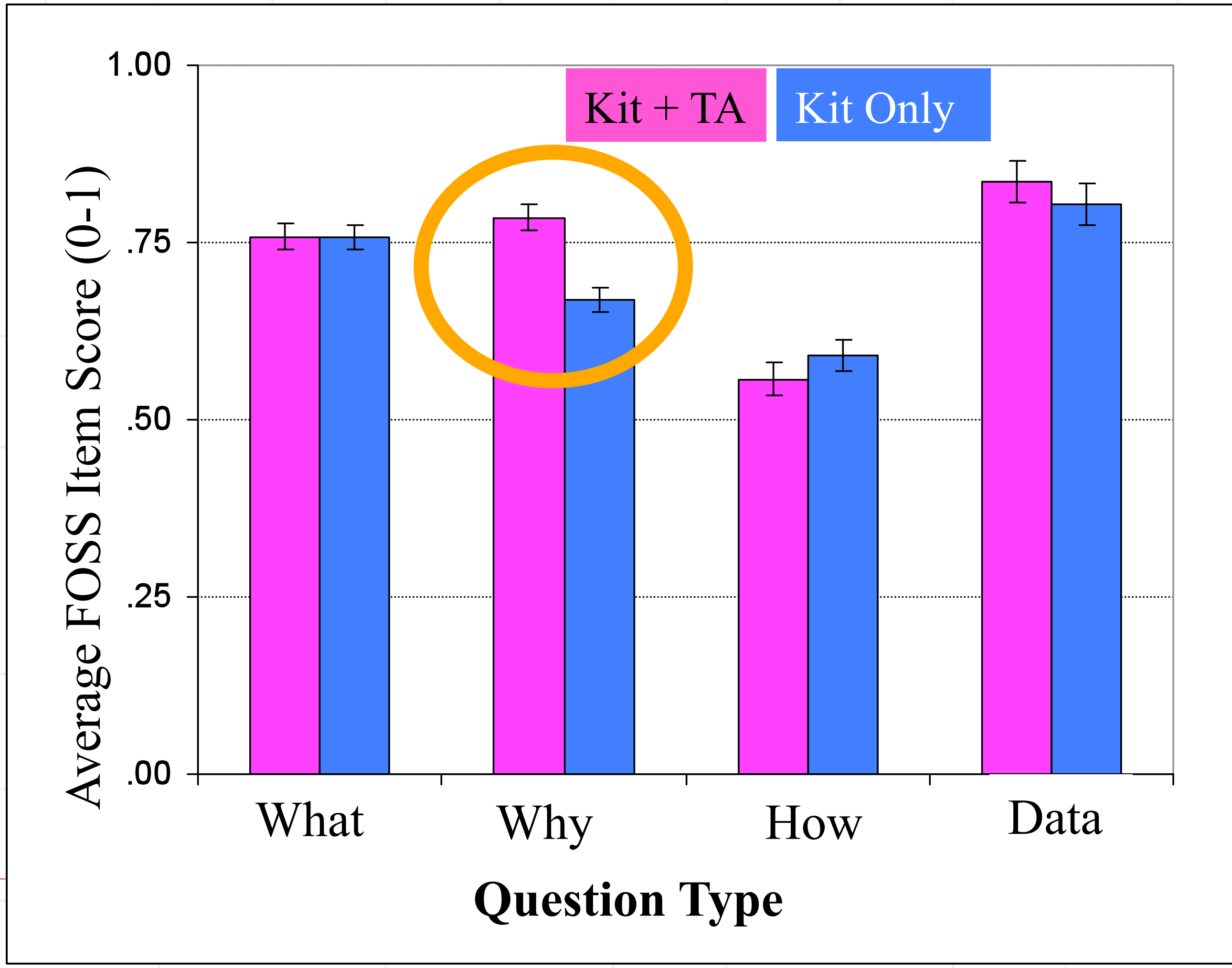
Half of teachers also used TA's as they wished.

Same total time overall.

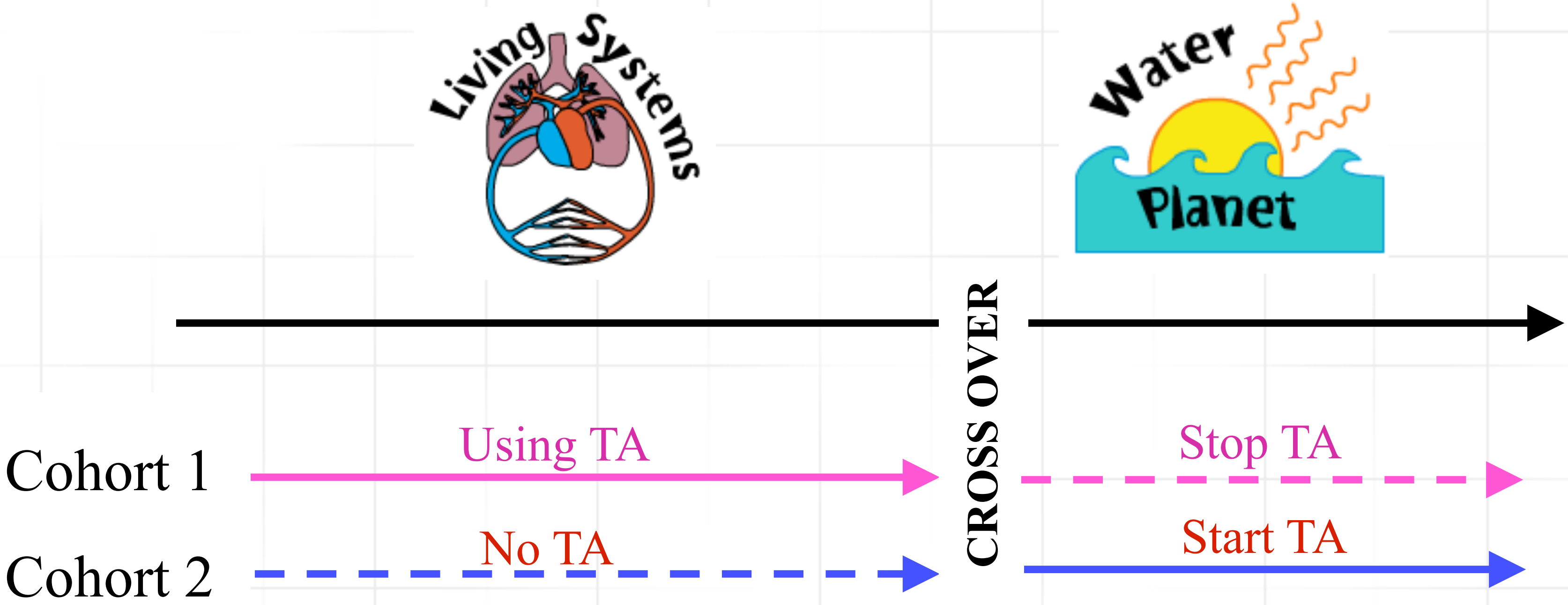
Cohort 1 — Using TA

Cohort 2 — No TA

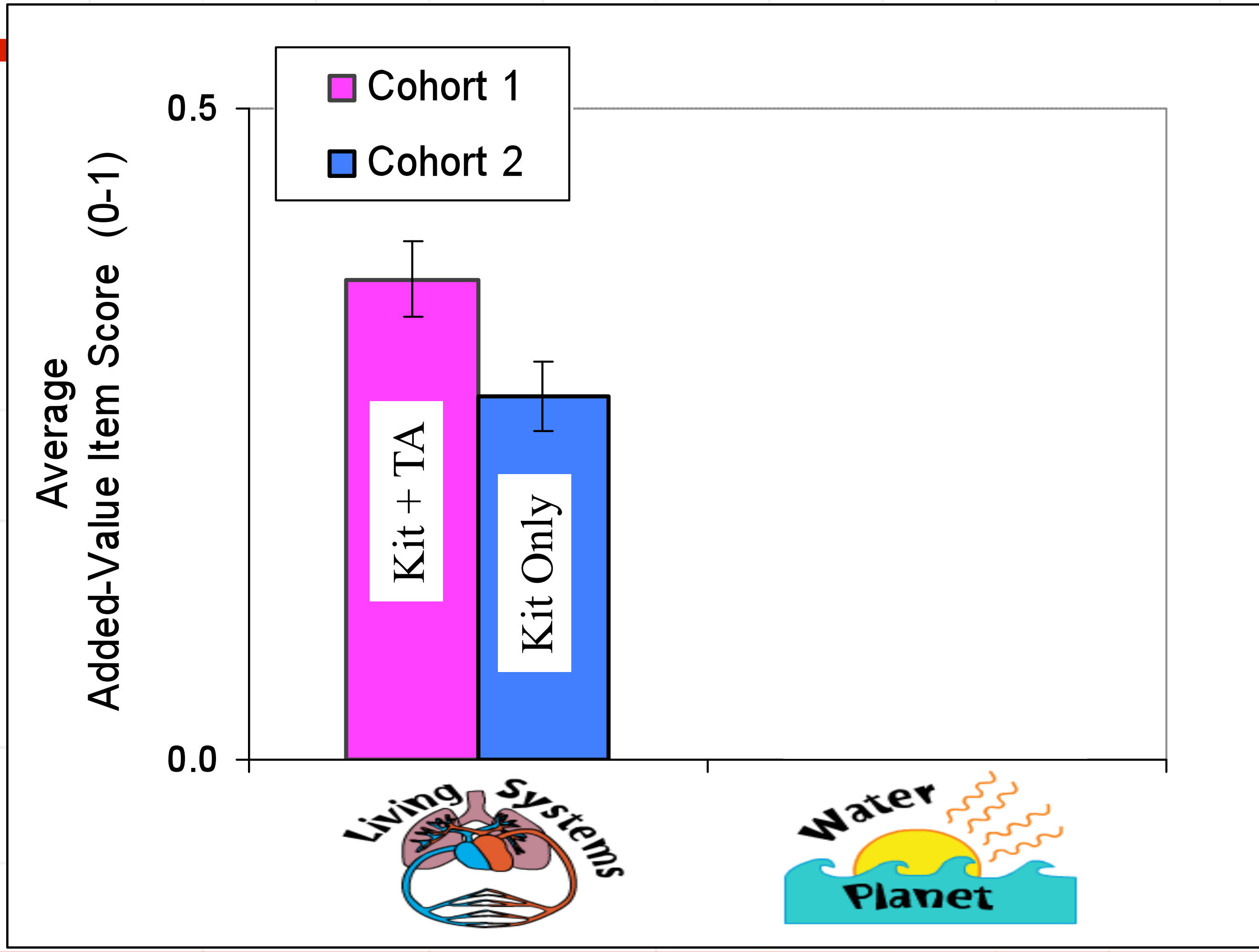
TA did not "hurt" students based on science kit's own test. TA did improve causal reasoning.



Are TA Learning Benefits Sustained?



Benefits for Learning Causal Relations Persists when Technology is Gone.



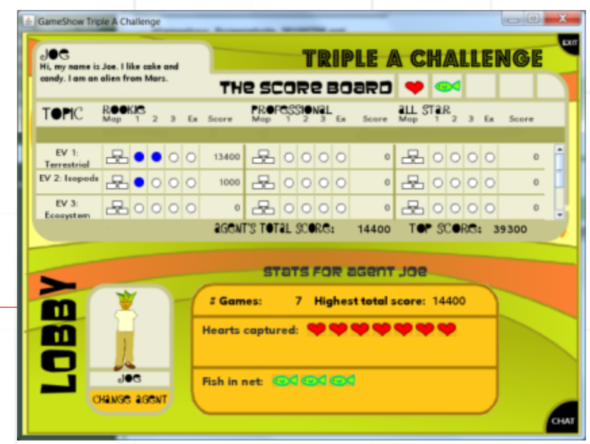
TA prepared kids for future learning.

Different Models of Translating with Teachable Agents

- Translation Research
  - Science of Context
  - Specifying Effects
  - Iterative Refinement

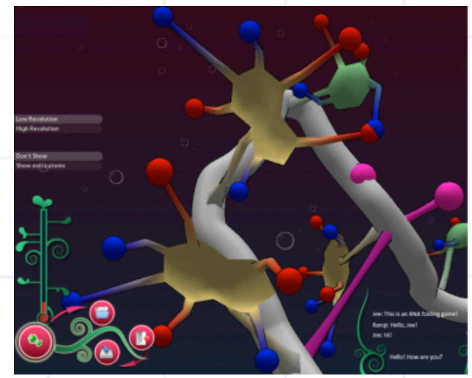
Iterative Refinement

- Design-based research
  - Keep refining in the midst of an intervention.
  - User testing is not a bad analogy.
- Experimental comparison of refinement/ extensions.
  - Taxonomy (4th-grade)/ Causality (5th-grade)
  - Reward v. No Reward



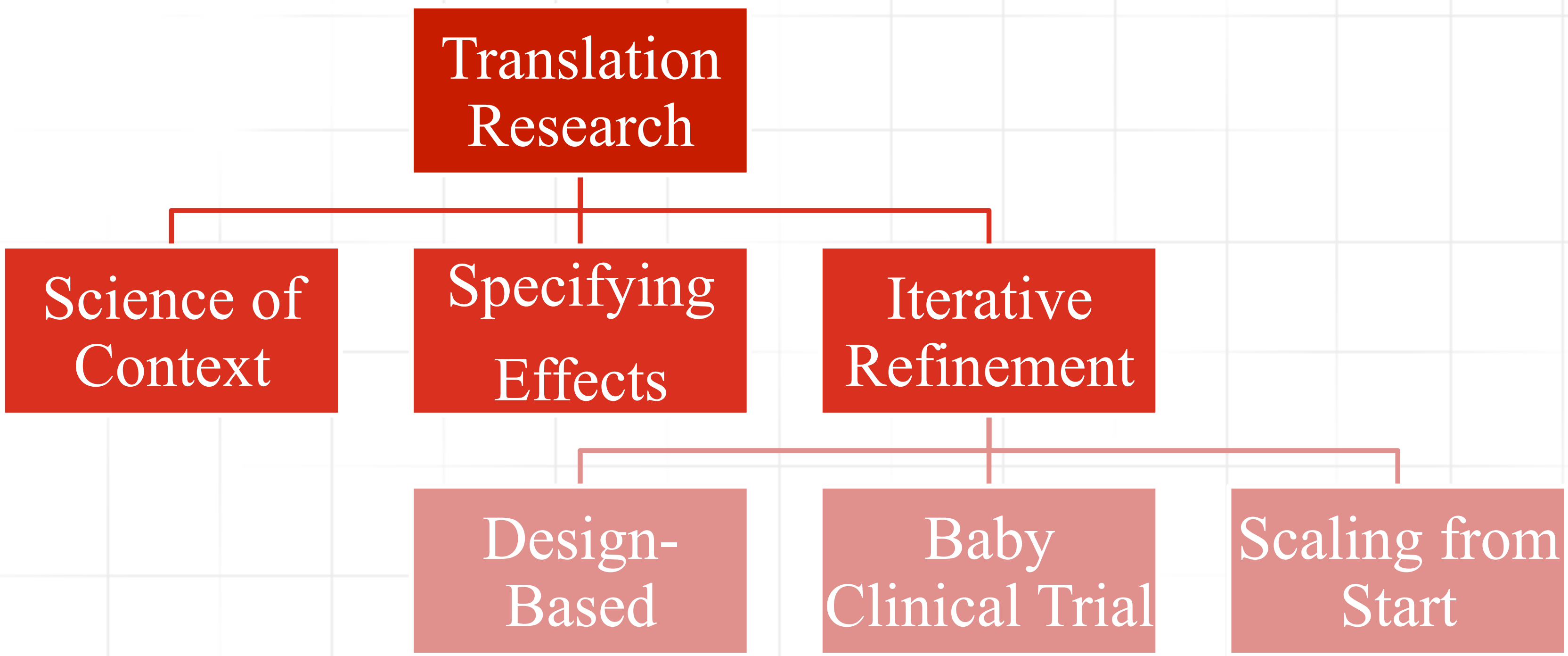
Letting go of the baby clinical trial model so considerations of "scale" are involved early on.

- Crowd sourcing is a new way to gather "human intelligence" data.
  - EteRNA
    - 10,000 users play games that involve protein folding.
    - Their "gaming" drives scientific research



- Kid-Sourcing Assessments of Learning
  - We are building infrastructure so that we and others can post assessments that target 21st century skills and others.
  - Ideally, very many children will want to play the "games" on-line.
  - We are developing methods for analyzing their in-game choices:
    - To determine effective and ineffective choice patterns for learning.
    - To refine assessments so they are maximally effective.
    - To improve learning while using the assessment.

In sum: Models of Translation Research Encountered so Far.



Abstract

Translational research is the central goal of the Pittsburgh Science of Learning Center (PSLC). That goal is motivated, on one hand, by the low rate of success (<10%) of large-scale randomized field trials of educational practices and, on other hand, by the lack of specificity, and corresponding lack of general up-take in educational practice, of purported general principles of learning coming from basic cognitive science research. We have facilitated the use of a research method called "in vivo experimentation" that is a translational stepping stone between laboratory experiments, which have limited ecological and external validity, and randomized field trials, which have limited internal validity. At the same time we are supporting cumulative development of theories of domain-general learning and domain-specific knowledge.

A key reason why laboratory-supported principles often do not translate reliably to the classroom is that there are unrecognized dependencies between the to-be-learned knowledge and the laboratory-supported principle. For instance, although there is strong lab support for the "multimedia principle" (i.e., scientific or mechanical processes are better learned from a combination of text and diagrams than from text alone), a careful application of that principle in a large-scale /in vivo /experiment in a college chemistry course produced a null result. A follow-up cognitive task analysis yielded a detailed theory of the domain-specific knowledge demands in this area of chemistry and application of this theory, alone and in combination with the multimedia principle, produced reliably better learning. Other PSLC research has also demonstrated limitations of purported general principles (e.g., self-explanation) that implicate knowledge analysis as the key theoretical tool needed to differentiate when the principle will work or not. PSLC has developed the Knowledge-Learning-Instruction (KLI) framework to refine principles of learning and instruction in terms of theories of domain-specific knowledge. In this session, we focus particularly on the role of knowledge component analysis in effective instructional design and, more generally, in supporting reliably effective translational research on learning.

In vivo experiments and cumulative theory as keys to translation

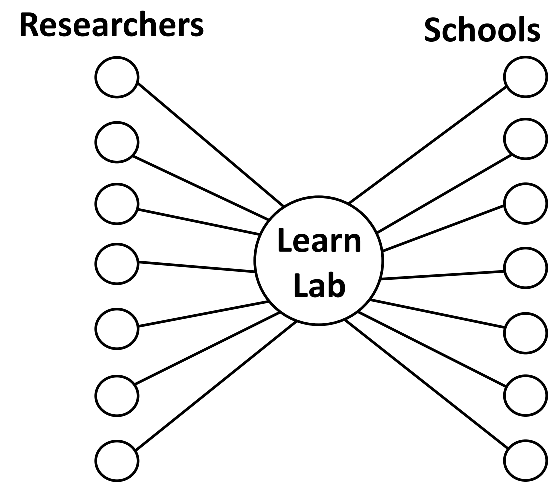
Ken Koedinger
PI of Pittsburgh Science of Learning Center (PSLC)
Professor of Human-Computer Interaction & Psychology, Carnegie Mellon University
Co-founder of Carnegie Learning, Inc.

LearnLab
Pittsburgh Science of Learning Center

PSLC: Bridging learning science research and educational practice

- Translational research is central goal
- Motivations
  - Low rate of success (<10%) of large-scale randomized field trials of educational practices
  - Lack of specificity of purported general principles
    - ⇒lack of general up-take in educational practice

⇒ Complexity of problem warrants center-level efforts



In vivo experimentation

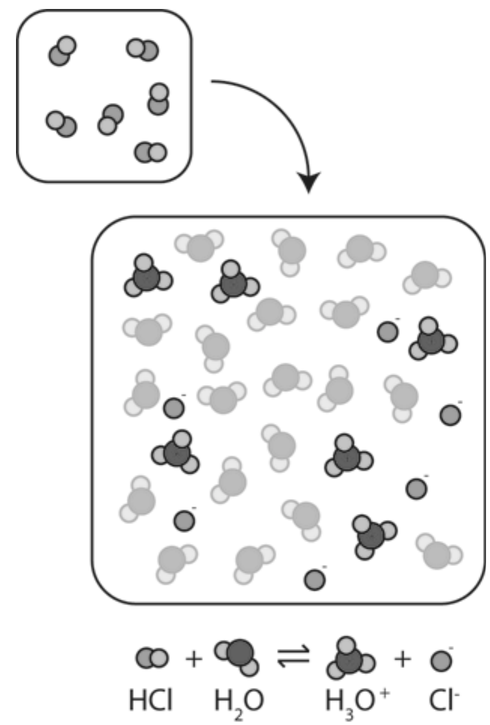
- Principle-testing controlled experiments run within courses

- Bridge between lab & field trials and their limitations
  – Lab experiments: Does effect generalize to real?
  – Randomized field trials: What *is it* that works?

Lab results don't simply generalize

- Mayer's multimedia principle
  - "combine graphical presentations … that illustrate key processes and concepts with verbal descriptions …" (IES Practice Guide)
  - Lab evidence: 89% gain, 1.5 effect, 9 of 9 studies

- Large-scale *in vivo* experiment in Chemistry LearnLab course
  - N=1139 ➔ Null effect
  - No evidence that combining molecular-level diagrams with text increases learning of chemical equilibrium



Jodi Davenport (Psych) , David Yaron (Chem), David Klahr (Psych), Ken Koedinger (HCI, Psych)

Cumulative Theory Development

Two domains of relevant theory

- Domain-general learning principles
- Domain-specific knowledge analysis

Effective translation requires both

Knowledge Analysis

- Key question: What knowledge components differentiate experts & novices?
  - Problem *representation* knowledge
  - Reasoning *strategy* knowledge

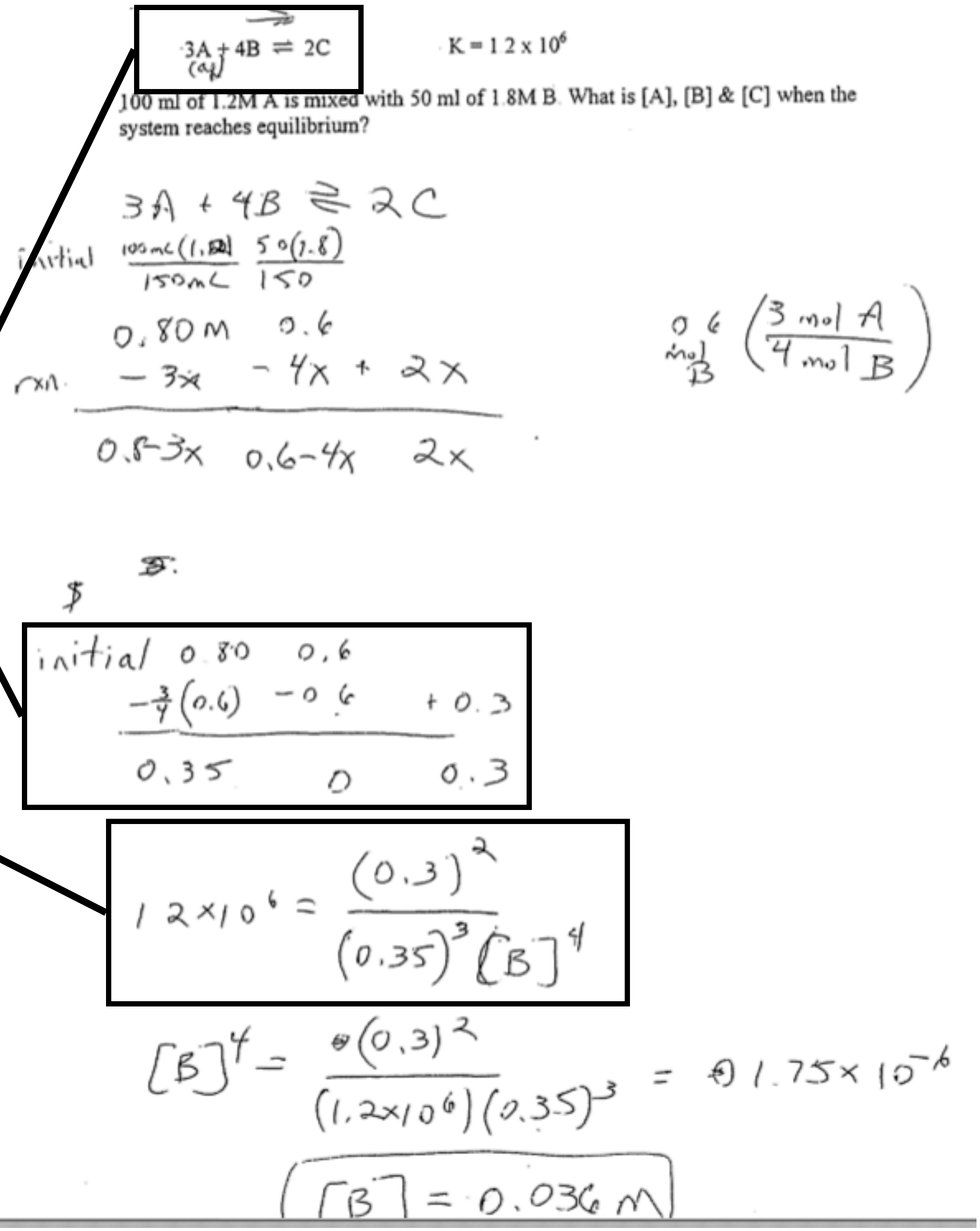
- Method:
  Think-aloud studies with 5 Chemistry experts (professors) & 9 novices (advanced students)

Jodi Davenport (Psych) , David Yaron (Chem), Klahr (Psych), Koedinger (HCI, Psych), Jim Greeno (Ed)

Experts

Reasoning Step
Considers progress of reaction to determine equilibrium concentrations.

Deep features
Applies K with equilibrium values.



$3A_{(aq)} + 4B \rightleftharpoons 2C$ $\qquad K = 1.2 \times 10^6$

100 ml of 1.2M A is mixed with 50 ml of 1.8M B. What is [A], [B] & [C] when the system reaches equilibrium?

$3A + 4B \rightleftharpoons 2C$

initial $\frac{100\,mL(1.2)}{150\,mL}$ $\quad \frac{50(1.8)}{150}$

$0.80\,M \quad 0.6$

rxn $-3x \quad -4x \quad +2x$

$0.8-3x \quad 0.6-4x \quad 2x$

$0.6 \text{ mol } B \left(\frac{3 \text{ mol } A}{4 \text{ mol } B}\right)$

initial $0.80 \quad 0.6$

$-\frac{3}{4}(0.6) \quad -0.6 \quad +0.3$

$0.35 \quad 0 \quad 0.3$

$$1.2\times10^6 = \frac{(0.3)^2}{(0.35)^3[B]^4}$$

$$[B]^4 = \frac{(0.3)^2}{(1.2\times10^6)(0.35)^3} = 1.75\times10^{-6}$$

$[B] = 0.036\,M$

Novice

$$\frac{[C]^2}{[A]^3\ [B]^4} = 1.2 \times 10^6$$

Shallow Features
Applies K expression with Non-Equilibrium values to solve for [C].

$$\frac{[C]^2}{[.100L \cdot 1.2]^3 [0.050L \cdot 1.8M]^4} = 1.2 \times 10^6$$

$$\frac{[C]^2}{1.728 \times 10^{-3} \cdot 6.561 \times 10^{-5}} = 1.2 \times 10^6$$

$$[C]^2 = 1.362 \times 10^{-1}$$

$$[C] = 3.69 \times 10^{-1}\,\underline{M}$$

$$[A] =$$

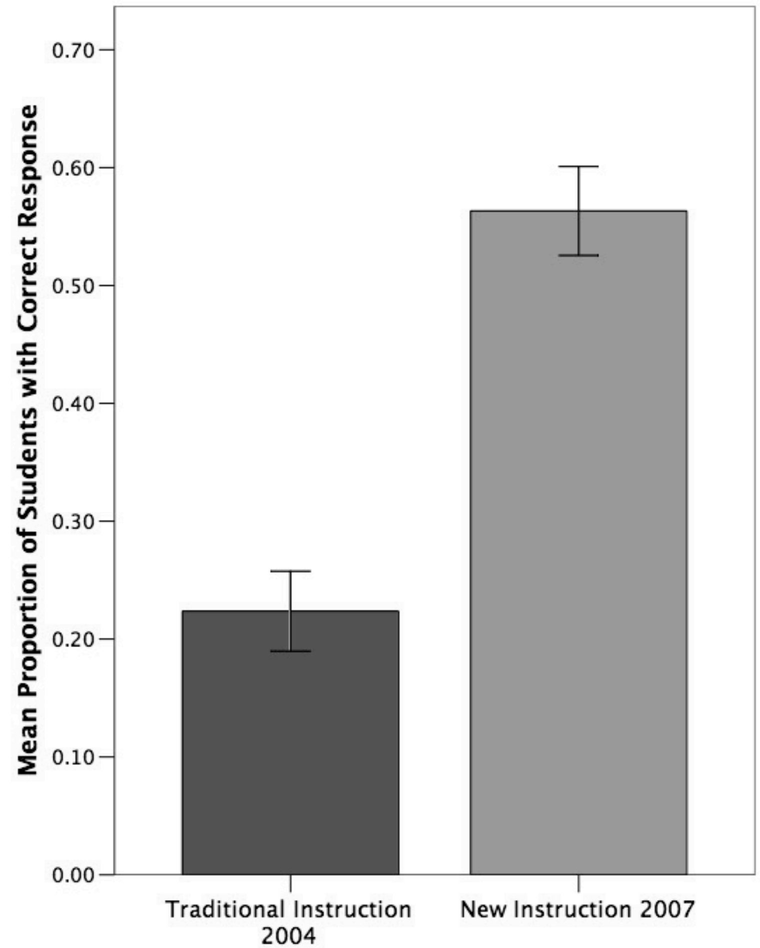
Experts (E) more deeply represent & reason than novices (N)

	Reasoning (Approx K ≈ infinity) Sub-optimal	Sophisticated
Shallow encoding (initial values in formula)	5 N	
Deep encoding (equilibrium vals in formula)	4 N 3 E	2 E

Jodi Davenport (Psych) , David Yaron (Chem), Klahr (Psych), Koedinger (HCI, Psych), Jim Greeno (Ed)

Redesign instruction based on knowledge analysis

- Make *progress of reaction* more explicitly tied to formulas & reasoning
- *Redesign led to ~2.5x improvement in equilibrium problem-solving on exam.*

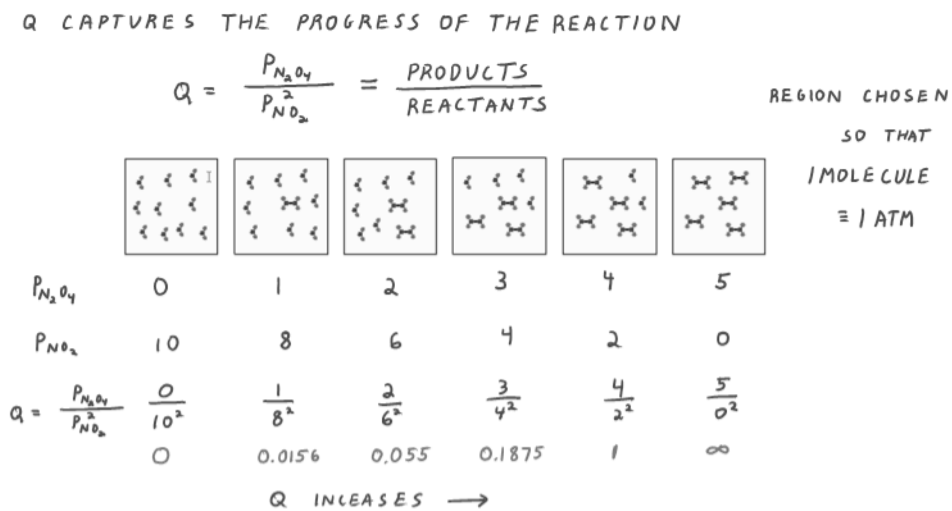


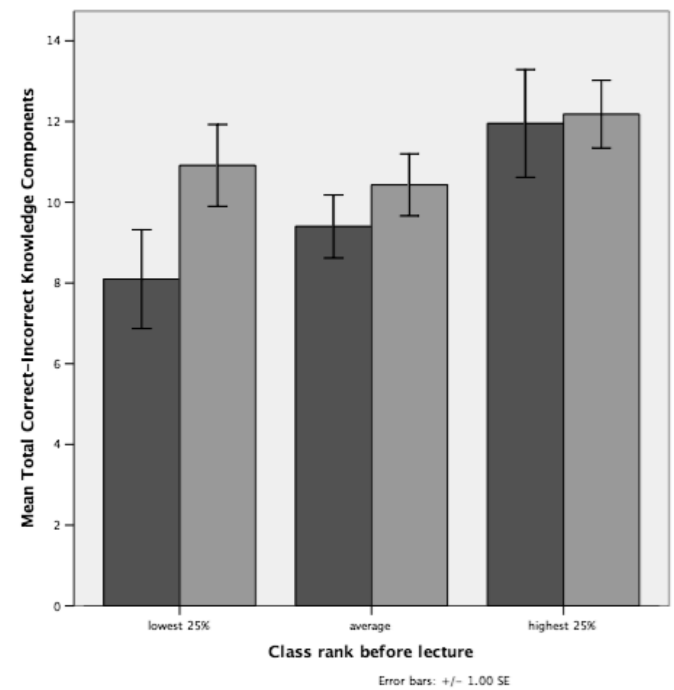
Cross-year comparison of Equilibrium Calculation Exam Performance

Error bars: +/- 1.00 SE

Jodi Davenport (Psych) , David Yaron (Chem), Klahr (Psych), Koedinger (HCI, Psych), Jim Greeno (Ed)

With new “progress of reaction” diagrams, further positive effect





Now, multimedia principle works

Effects are strongest for struggling students

Cognitive Science principles don't simply generalize to practice

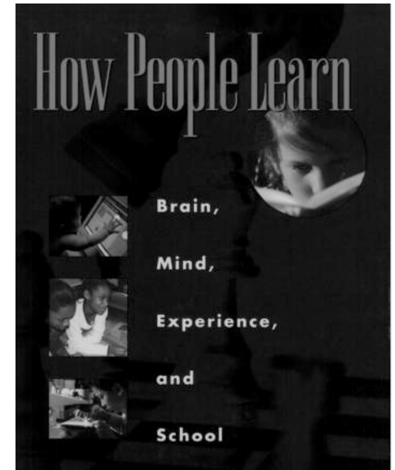
- From lab tasks to academic content
  - A cognitive task analysis of *domain knowledge* may be required
- From initial domains to new domains
  - Knowledge-specific constraints may limit generality

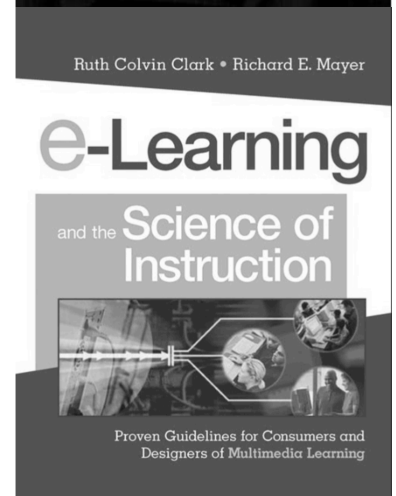
$\Rightarrow$Need to specify *dependencies* between general principles & domain knowledge

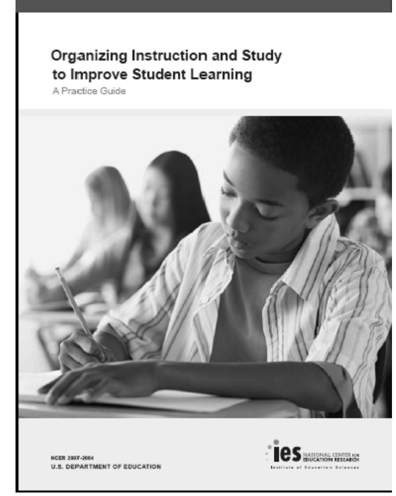
Principles, assistance dilemma

- More assistance vs. more difficulty
  - Massed vs. *distributed* (Pashler)
  - Study vs. *test* (Roediger)
  - *Examples* vs. problem solving (Sweller)
  - *Direct instruction* vs. discovery (Klahr)
  - Re-explain vs. *ask for explanation* (Chi)
  - *Immediate* vs. *delayed* (Anderson vs. Bjork)
  - *Concrete* vs. *abstract* (Pavio vs. Kaminski)
  - …

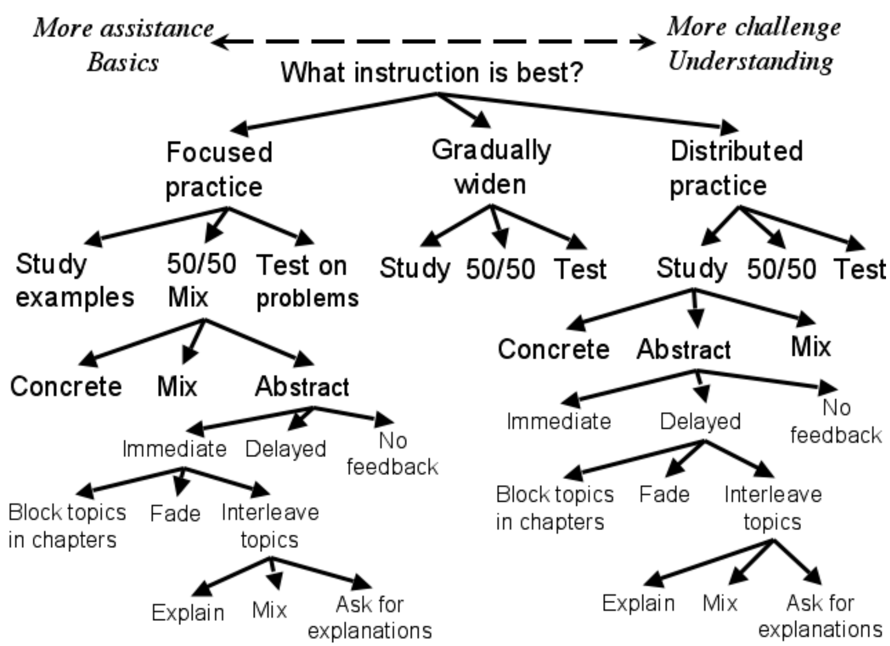
- More theory & data is needed!







Huge space of possible instructional options – which work best?



205,891,132,094,649

3^{15*2}

Evidence is not strong enough

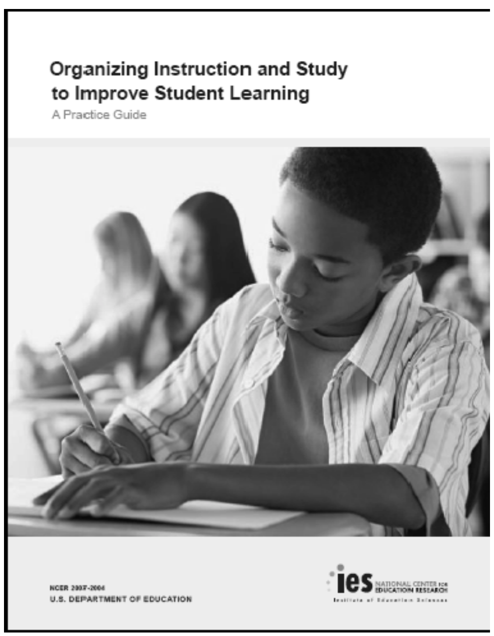


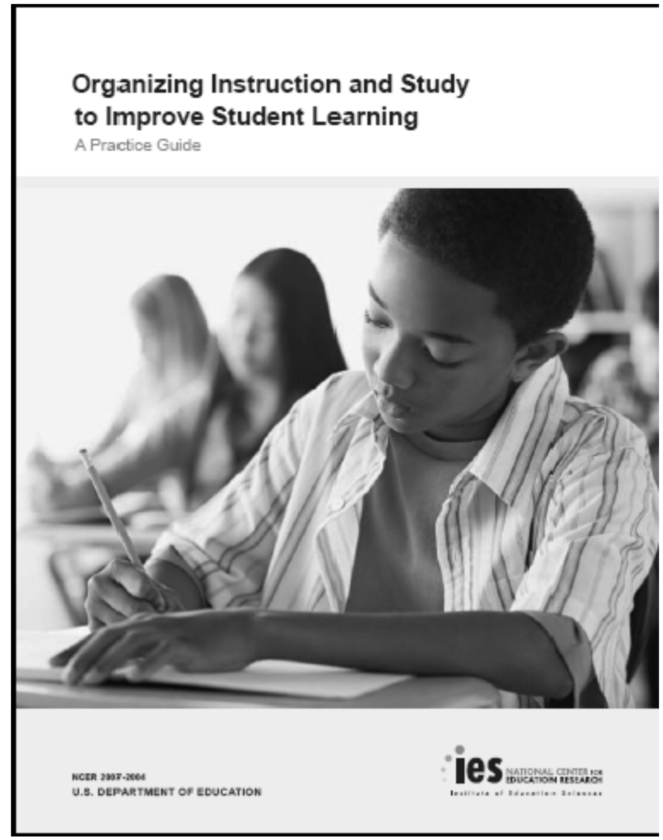
Table 2. Recommendations and corresponding Level of Evidence to support each

Recommendation	Level of Evidence
1. Space learning over time. *Arrange to review key elements of course content after a delay of several weeks to several months after initial presentation.*	**Moderate**
2. Interleave worked example solutions with problem solving exercises. *Have students alternate between reading already worked solutions and trying to solve problems on their own.*	**Moderate**
3. Combine graphics with verbal descriptions. *Combine graphical presentations (e.g., graphs, figures) that illustrate key processes and procedures with verbal descriptions.*	**Moderate**
4. Connect and integrate abstract and concrete representations of concepts. *Connect and integrate abstract representations of a concept with concrete representations of the same concept.*	**Moderate**
5. Use quizzing to promote learning. *Use quizzing with active retrieval of information at all phases of the learning process to exploit the ability of retrieval directly to facilitate long-lasting memory traces.*	**5a. Low**
5a. *Use pre-questions to introduce a new topic* 5b. *Use quizzes to re-expose students to key content*	**5b. Strong**
6. Help students allocate study time efficiently. *Assist students in identifying what material they know well, and what needs further study, by teaching children how to judge what they have learned.*	**6a. Low**
6a. *Teach students how to use delayed judgments of learning to identify content that needs further study* 6b. *Use Tests and Quizzes to Identify Content that Needs to be Learned*	**6b. Low**
7. Ask deep explanatory questions. *Use instructional prompts that encourage students to pose and answer "deep-level" questions on course material. These questions enable students to respond with explanations and supports deep understanding of taught material.*	**7. Strong**

Cognitive science principle: Prompt for self-explanation

Recommendation 7: Help students build explanations by asking and answering deep questions.

When students have acquired a basic set of knowledge about a particular topic of study and are ready to build a more complex understanding of a topic, we recommend that teachers find opportunities to ask questions and model answers to these questions, in order to help students build deep explanations of key concepts. By *deep* explanations we mean explanations that appeal to causal mechanisms, planning, well-reasoned arguments, and logic. Examples of deep explanations include those that inquire about causes and consequences of historical events, motivations of people involved in historical events, scientific evidence for particular theories,

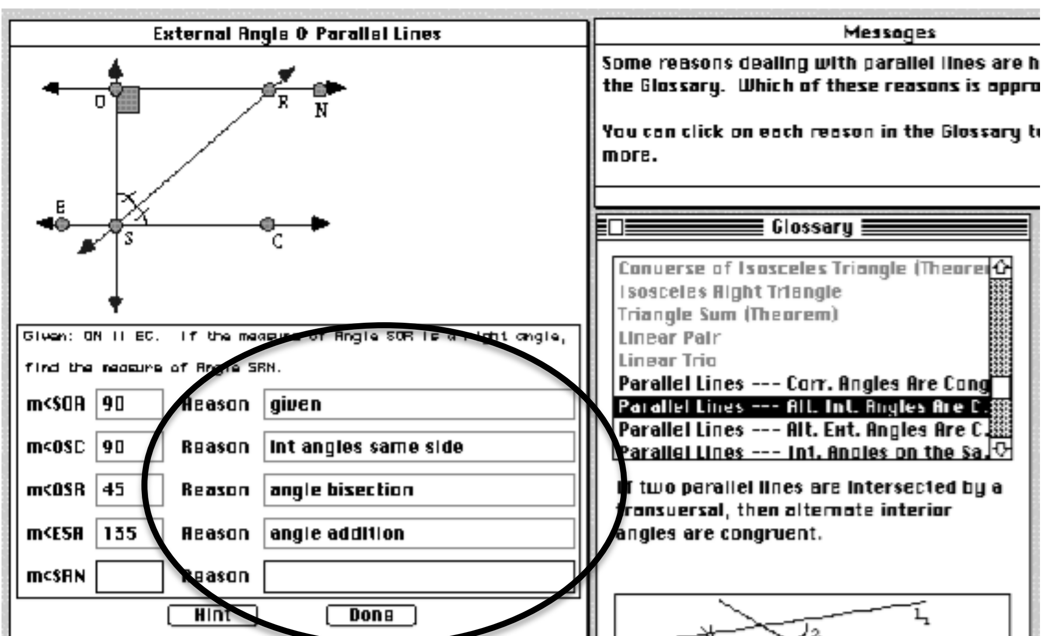


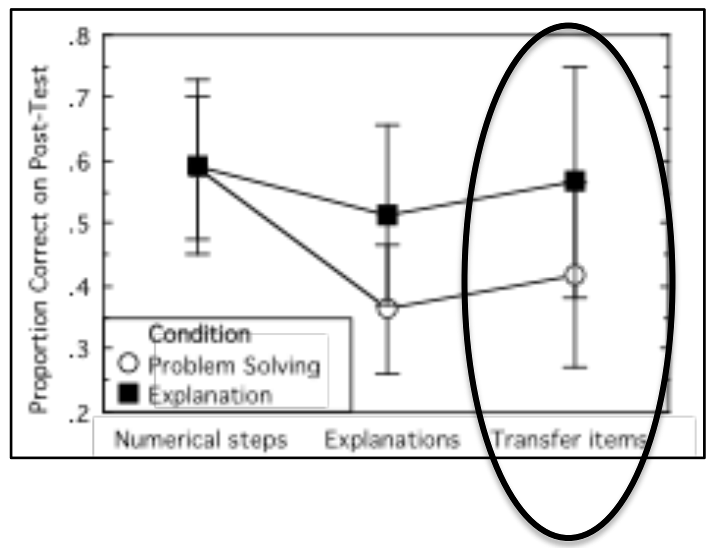
Among 2 of 9 rec's with "strong" evidence

- Many randomized controlled experiments in lab and in schools
  - Aleven & Koedinger (2002); Beck, McKeown, et al. (1997); Craig, Sullins, et al. (2006); Driscoll, Craig, et al. (2003); Gholson & Craig (2006); King (1992; 1994); Rosenshine, Meister, & Chapman (1996); Wisher & Graesser (2007)

PSLC: *In vivo* studies of self-explanation prompting

- In Physics, Geometry, Algebra, English courses
- LearnLab course committee support
- *Scalable solutions*





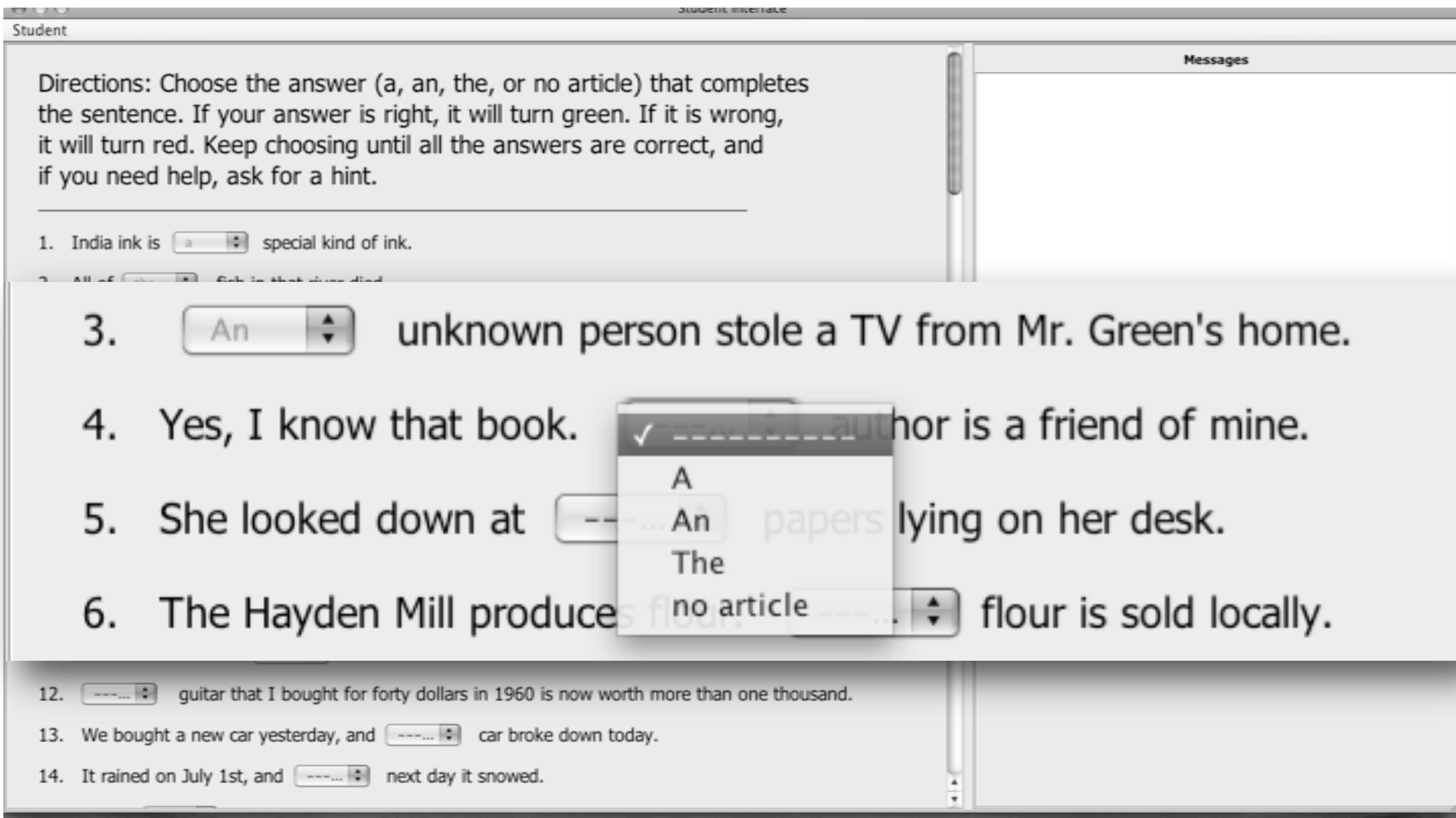
Generality claim

"Self-explanation is a domain general constructive activity that engages students in active learning and insures that learners attend to the material in a meaningful way while effectively monitoring their evolving understanding" (Roy & Chi, 2005)

In vivo experiment in English LearnLab

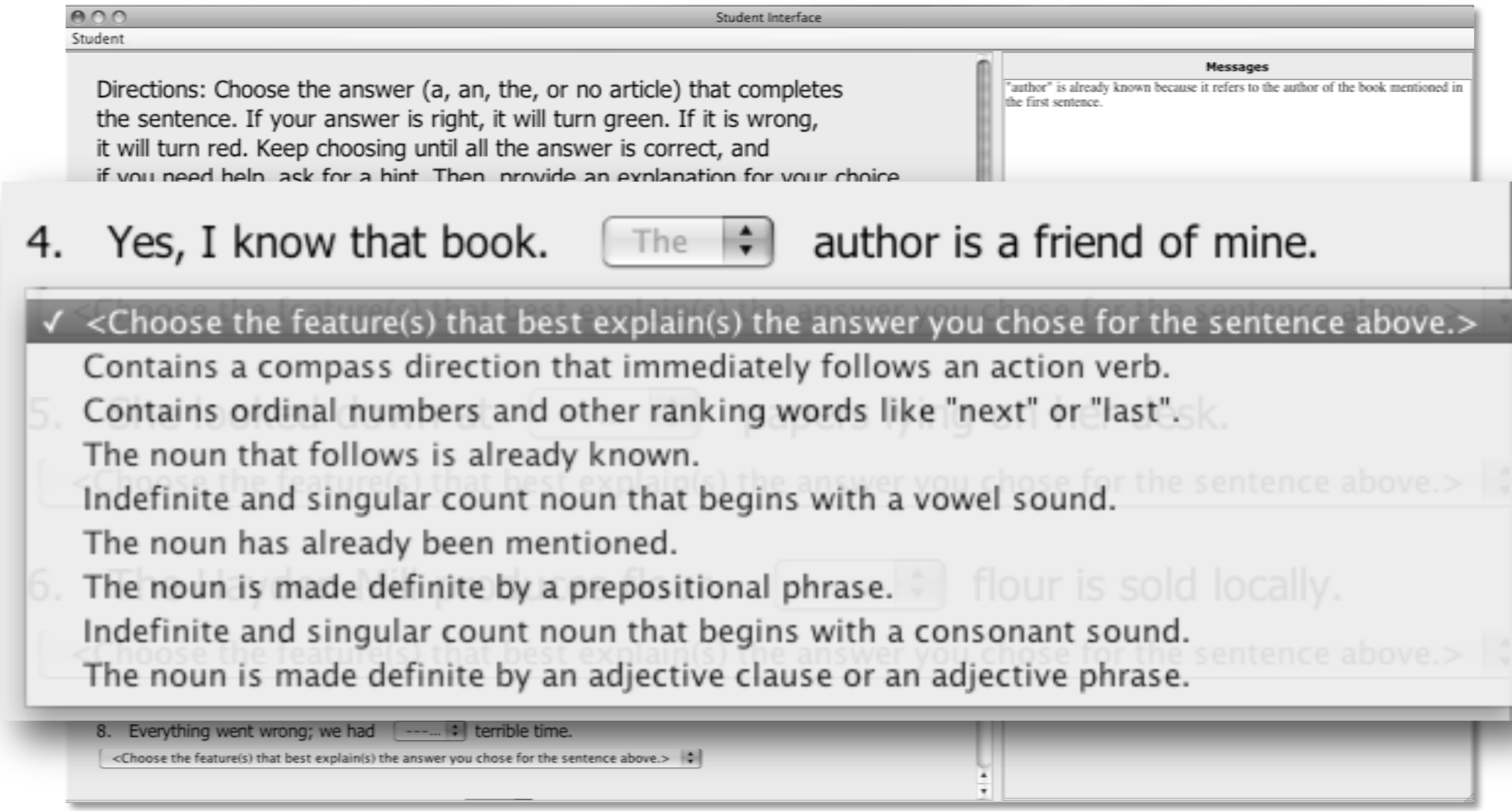
- Course
  - College-level English as a Second Language
  - Grammar section of levels 3, 4, and 5
- Setting: Regular class meeting in computer lab
- Assessments & incentives
  - Pre & post embedded in computer-based activity, downstream exams include relevant items
  - Class participation grade, material is on test, students want to proficient in English
- Target content: English article grammar

Practice only



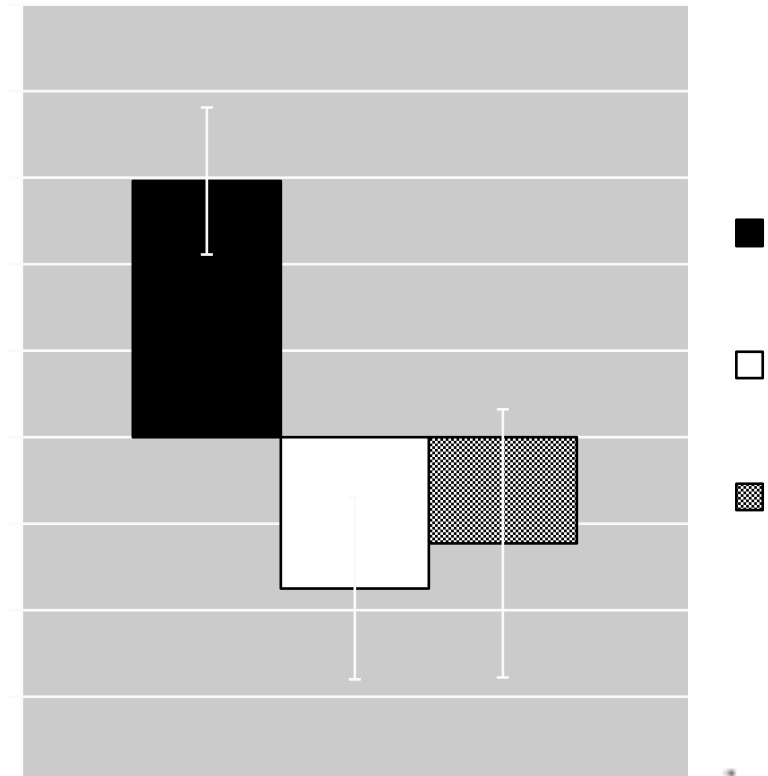
Ruth Wylie (HCI) , Teruko Mitamura (LTI), Ken Koedinger (HCI, Psych)

Self-Explanation (menu)



More efficient learning from practice *without* self-explanation

Learning Efficiency



$$Efficiency = Z(gain) - Z(time)$$

Learning Efficiency =
z-score(post-pre) - z-score(learning-time)

p = 0.01

Knowledge-Learning-Instruction (KLI) framework

- Refine principles of learning & instruction in terms of theories of knowledge
- Different kinds of knowledge
  => different learning processes
  => differences in optimal instruction

Task Features	Response	Relationship	Rationale	Labels
constant	constant	implicit	no	association
constant	constant	explicit	no	fact
variable	constant	implicit	no	category
variable	constant	explicit	no	concept
variable	variable	implicit	no	production, schema, skill
variable	variable	explicit	no	rule
variable	variable	explicit	yes	principle, rule, model

Self-explanation hurts

Unknown

Self-explanation helps

Keys to Translational Research on Learning & Education

- Method: *In vivo* experiment as bridge
  - 150+ in math, science, 2nd language courses
  - New IES Math Center taking to next step
    - includes two former PSLC postdocs!
- Theory: Domain-specific knowledge analysis to select & reference domain-general principles of learning and instruction
  - Get KLI framework paper at learnlab.org

Next two talks:
More PSLC examples of translation

Themes

- Adapting general learning principles to specific academic content
  - Knowledge component analysis is critical
- *In vivo* experiments to test, refine, improve

END

From Research to Practice: Interactive Examples and Diagrammatic Self-explanation in an Intelligent Tutoring System

Vincent Aleven
Human-Computer Interaction Institute
Carnegie Mellon University

Joint work with

Alexander Renkl
Department of Psychology
University of Freiburg
Freiburg, Germany

Rolf Schwonke
Department of Psychology
University of Freiburg
Freiburg, Germany

Joint work with

Ron Salden
Madera Interactive Technologies Institute
University of Madeira

Kirsten Butcher
Department of Educational Psychology
University of Utah

LearnLab
Pittsburgh Science of Learning Center

Abstract

Intelligent tutoring systems have been proven to enhance students' mathematics learning in high schools and middle schools, compared to typical curricula without such software. These tutors support the learning of a complex cognitive skill through guided practice. A central component of each tutor is its cognitive model, which captures the detailed knowledge components (KCs) that make up the targeted cognitive skill. These models are a main form of knowledge componential analysis, which features centrally in the PSLC's theoretical framework.

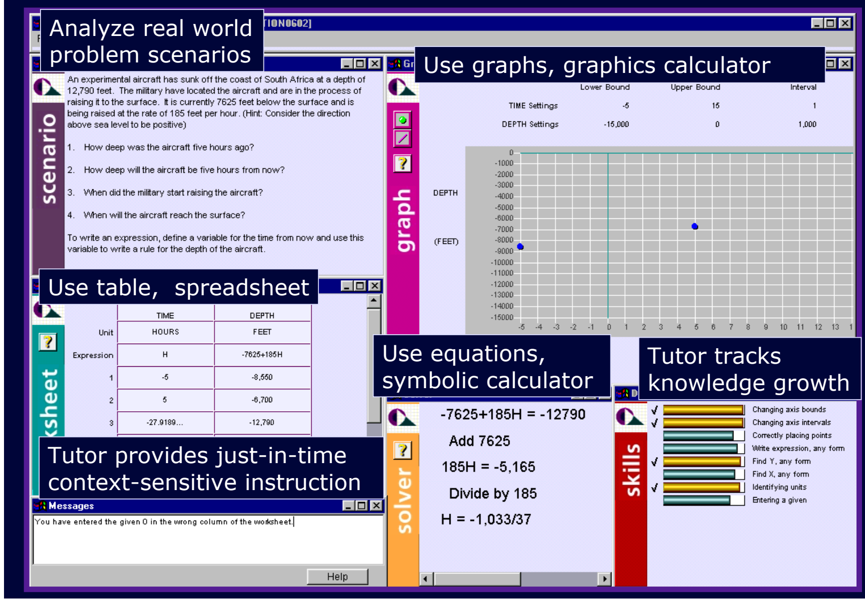
Traditionally, tutors have used their cognitive models to implement a form of fine-grained, individualized mastery learning. In this presentation, we review results from in vivo studies that demonstrate additional ways in which a model based on KC analysis can improve robust learning with a tutor. These studies tested instructional principles while at the same time aiming to improve the effectiveness of the Geometry Cognitive Tutor, a commercially-available intelligent tutoring system originally developed by our research group. One series of studies demonstrated the effectiveness of adaptive example fading based on KC modeling. The second showed that KC-specific prompts for diagrammatic self-explanations lead to more robust student learning.

The research underlines the value of KC analysis for improving robust learning in real-world domains. The research is translational in the following ways: First, it uses as platform an intelligent tutoring system that has successfully made the transition from research to practice. Second, software features proven to be effective in this research have since been incorporated in commercially available versions of the tutor.

Introduction

- Prior talk: KC analysis is key in implementing instructional principles in real classrooms
- KC analysis facilitates implementation of
  - Worked Examples Principle and
  - Visual-Verbal Integration Principle
- Intelligent tutoring systems (ITSs): example of translational research based on KC analysis

Algebra Cognitive Tutor Example



Cognitive Tutor Math Courses Making a Difference

The New York Times Technology

Software Tutors Offer Help and Customized Hints

Chris Maynard for The New York Times

MATH COACH - Rochelle Brown, left, and Iesha Antonetti, students at Middle School 103 in the Bronx, use Cognitive Tutor software to reinforce math skills. The software is designed to give students individualized instruction when personal attention is scarce.

- Real-world impact of Cognitive Tutors
  - Disseminated by spin-off company, Carnegie Learning, Inc.
  - 500,000 students per year!
- Faclitate further translational research
  - Cognitive Tutor classrooms are "LearnLabs"

Cognitive Tutor Technology:

KC analysis key to individualizing instruction

- Cognitive Model: A system that can solve problems in the various ways students can
- Captures the KCs

Strategy 1: IF the goal is to solve a(bx+c) = d
THEN rewrite this as abx + ac = d

Strategy 2: IF the goal is to solve a(bx+c) = d
THEN rewrite this as bx + c = d/a

Misconception: IF the goal is to solve a(bx+c) = d
THEN rewrite this as abx + c = d

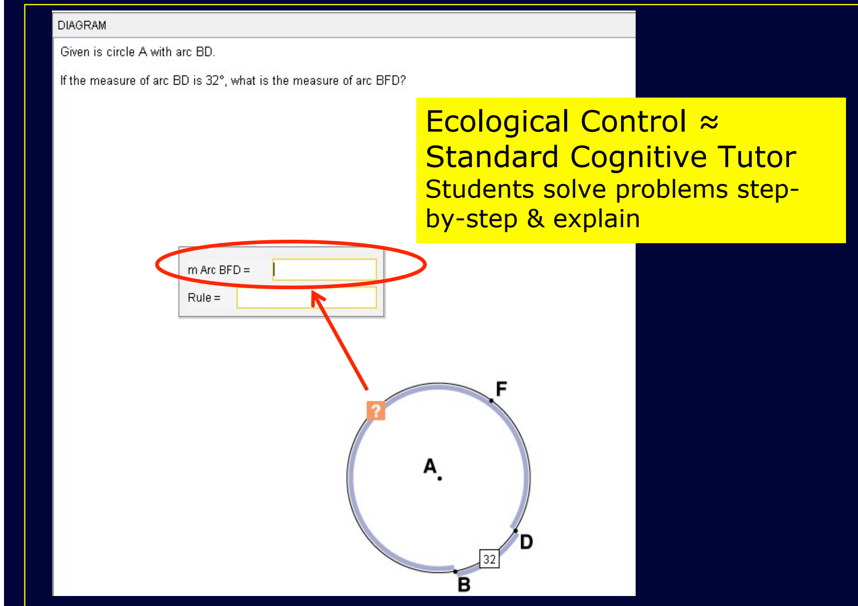
Book on ACT-R theory: Anderson, J. R., & Lebière, C. (1998). *The Atomic Components of Thought.* Mahwah, NJ: Erlbaum.

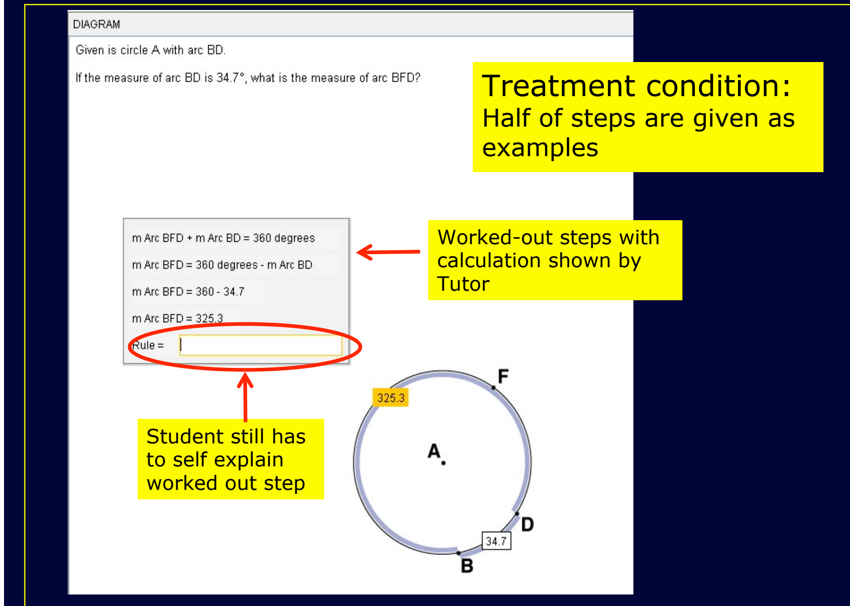
Worked Examples Principle

- In contrast to the traditional approach of giving students a list of homework (or seatwork) problems to solve, students learn more efficiently and more robustly when more frequent study of worked examples is combined with problem solving practice.

Research questions

- Are examples effective in learning environments *with tutoring?*
- (How) can KC analysis help in devising a scheme for *adaptively* fading examples?





Fixed Fading: At the KC level

	Problem Solving			Examples		
Problems	**KC_1**	**KC_2**	**KC_3**	**KC_1**	**KC_2**	**KC_3**
P_1	PS			Ex		
P_2		PS			Ex	
P_3			PS			Ex
P_4	PS	PS	PS	Ex	Ex	Ex
P_5	PS	PS	PS	PS	Ex	Ex
P_6	PS	PS	PS	PS	PS	Ex
P_7	PS	PS	PS	PS	PS	PS

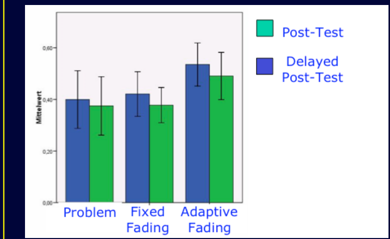
__Ex:__ worked-out example step; __PS:__ problem-solving step

Adaptive Fading

- Goal: individualized transition points from examples to problems
- Transition when student has a moderate ability to explain steps with the given KC
- KC analysis is key
  - System tracks each student's mastery of each KC
  - When presenting a new problem, decides on the fly, which steps should be worked-out

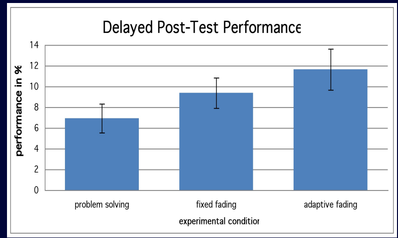
Results

Lab study (Freiburg)



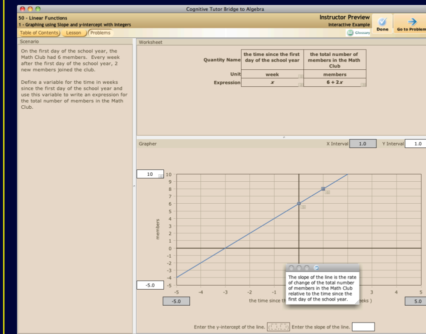
- Post-test & delayed post-test: Adaptive Fading condition showed better far transfer than the two control conditions

In vivo study (Pittsburgh)

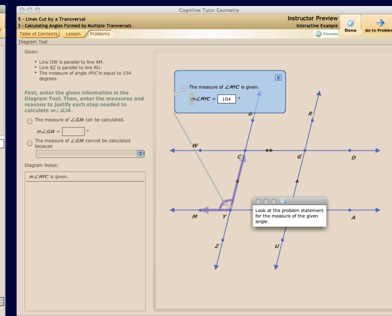


- At the delayed post-test, Adaptive Fading condition showed better overall performance and transfer than the Problem condition
- Effect size: 0.4 SD

Translation into Practice (Widely-used Curriculum)



Bridge to Algebra



Geometry Cognitive Tutor

Visual-Verbal Integration Principle

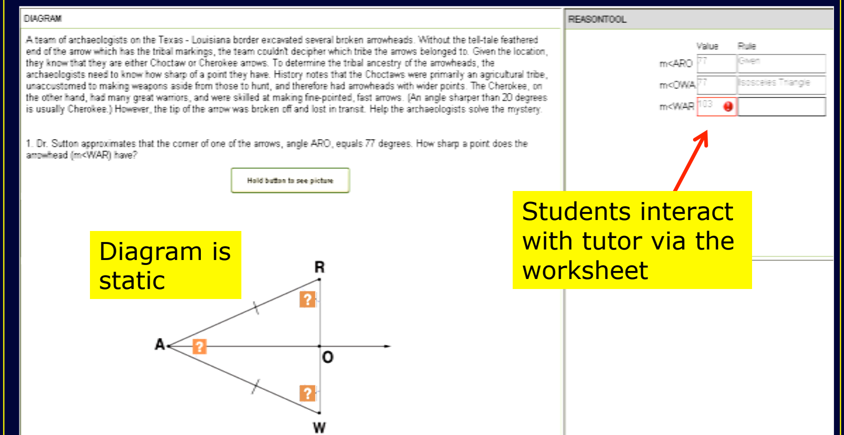
- Instruction that includes both visual and verbal information leads to … robust learning … only when the instruction supports learners as they coordinate information from both sources and the representations guide student attention to deep features.

Research Questions

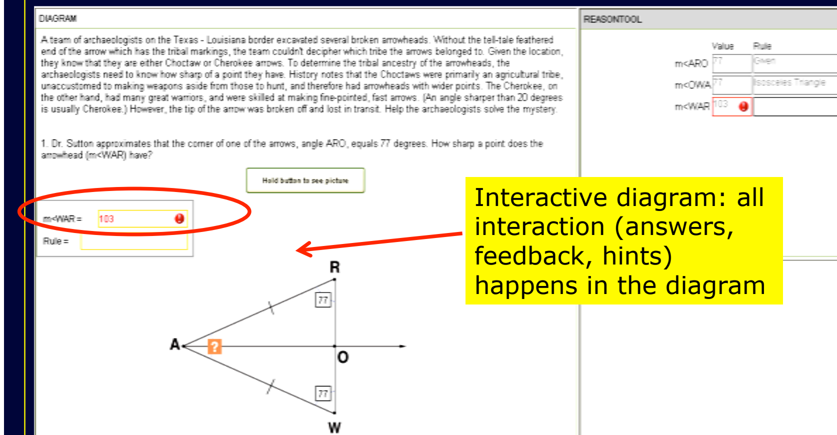
- Does
  - An interactive diagram that integrating visual and verbal information, and/or
  - Visual self-explanation of rule/diagram mapping

  lead to more robust learning?

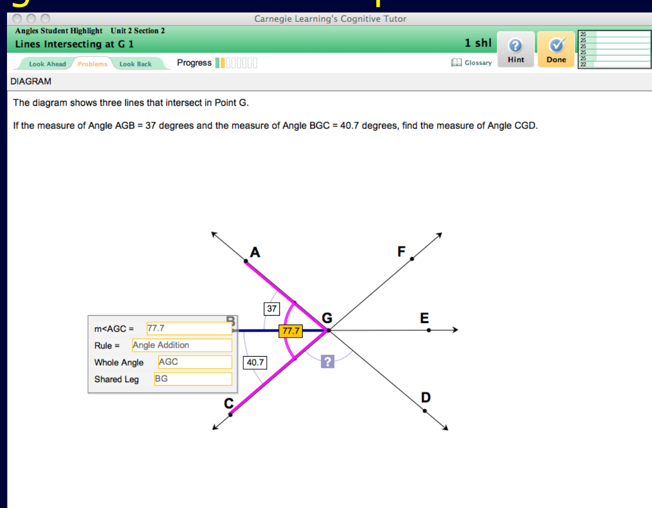
Control Condition: Separation of Visual/Verbal Information



Visual Verbal Integration(1): Interactive Diagram

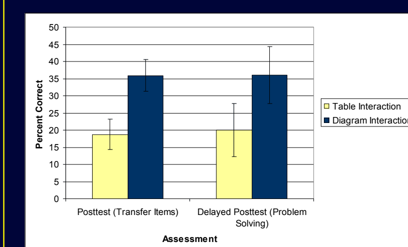


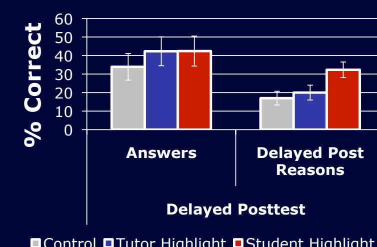
Visual-Verbal Integration (2): Diagrammatic Self-Explanation



Results

Visual-Verbal Integration





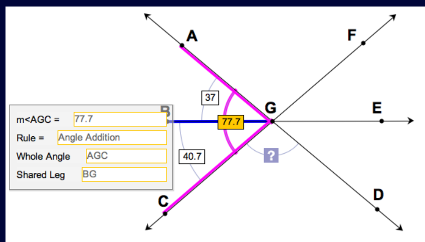
Interactive Diagram

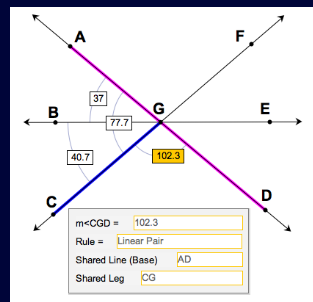
Effect size: 0.58 SD

Diagrammatic Self-Explanation

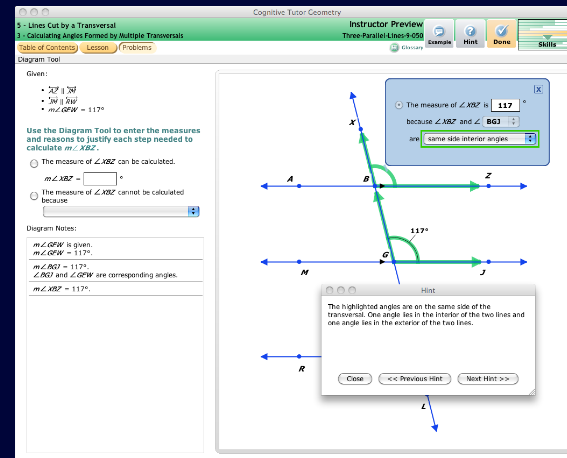
KC analysis helps

- Prompts Depend on KC





Translation into Practice (Widely-used Curriculum)



Conclusion

- KC analysis can facilitate implementation of instructional principles
- In novel and "translational" ways
  - Enhance student learning in actual classrooms
  - Transitioned into widely used curriculum

Classroom experiments with the TED Tutor:
Training in Experimental Design

Instructing & Assessing the Knowledge Components Comprising CVS

David Klahr

Pittsburgh Science of Learning Center

Department of Psychology

Program in Interdisciplinary Education Research (PIER)

Carnegie Mellon University

What is "CVS"?

CVS: Control of Variables Strategy

- A simple <u>procedure</u> for designing unconfounded experiments:
  - Vary one thing at a time (VOTAT).
- The <u>conceptual</u> basis for making valid inferences from data:
  - isolate causal path.

Why study CVS?

Theoretical reasons (basic research):

- Surface vs deep mapping during analogical transfer of procedures and concepts at different transfer "distances".
- Diagnosing and remediating misconceptions

Practical reasons (applied research):

<u>Topic:</u> Core topic in early science instruction

<u>Assessment:</u> State standards
High stakes assessments
NCLB is now testing science

<u>Most effective instructional approach for teaching CVS?</u>
Where to situate on the "direct instruction" vs "discovery" spectrum?
Heated controversy in profession
Legislative battles over science curriculum

Three instructional conditions

Aspect	"Direct"	"Socratic"	"Discovery"
Materials	Ramps, Springs, Sinking Objects		
Goal setting	By Teacher: can you find out whether X makes a difference in how far the ball rolls?"		
Physical manipulation of materials by child	Yes	Yes	Yes
Design of each experiment	Teacher	Student	Student
Probe questions	Yes	Yes	No
Explanations	Yes	No	No
Summary	Yes	No	No
Execution of experiments	No	Yes	Yes
Observation of outcomes	No	Yes	Yes

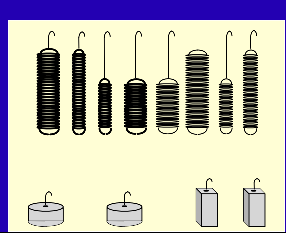
Example from early studies: Springs domain

Which attributes determine how far a spring will stretch?

<u>Materials</u>:
8 springs: 2 lengths x 2 widths x 2 wire sizes & 2 pair of weights

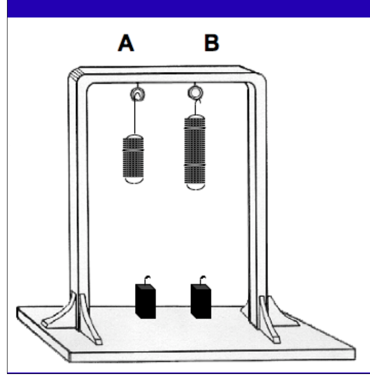
<u>Execution</u>:

- Select two springs
- Select two weights
- Hang springs on rack hooks
- Hang weights on springs.
- Compare amount of stretching.



Springs

An <u>unconfounded</u> test to determine whether spring length affects amount of stretching.



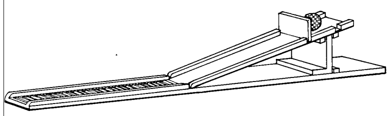
Length is "focal variable"

	A	B
Length:	**short**	**long**
Width:	**wide**	**wide**
Wire:	**thin**	**thin**
Weight:	**light**	**light**

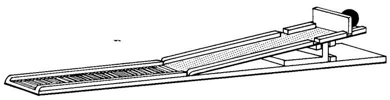
Ramps

An completely confounded test to determine whether ramp surface affects how far the ball rolls

Surface is "focal variable"



Surface: smooth
Run: short
Steepness: high
Ball: golf



Surface: rough
Run: long
Steepness: low
Ball: rubber

Lessons learned about middle school children and experimental design

(Chen & Klahr, 1999; Toth, Klahr, 2009; Klahr, & Chen, 2000; Klahr, & Nigam, 2004; Matlen & Klahr, 2010; Li, Klahr, & Siler, 2006; Strand-Cary, & Klahr, 2008;)

Do children know how to design "good" experiments? (CVS)
- No: In "good schools", ~40% of 3rd & 4th graders' simple experiments are unconfounded when they first encounter simple experimental design tasks. In "not so good schools" only 15% unconfounded.

Can they be taught?
- Yes: ~80% of 4th graders' experiments unconfounded following brief session of explicit instruction with probes and feedback.

What's a highly effective way to teach this topic?
- Explicit, focused instruction.

Consistent results from several studies

If CVS instruction:
- **Is Explicit, Didactic**
- **Provides "good" and "bad" examples**
- **Asks focused probe questions ("why is this a 'good'/'bad experiment?")**
- **And provides explicit answers, and explanations**

Then:
- **Students learn and transfer CVS knowledge:**
  - **Assessed on near transfer (similar experimental set ups)**
  - **Assessed on far transfer ("story" problems, months & years later)**

Lessons learned (continued)

Does learning CVS via "Direct Instruction" transfer to other materials, domains, & test formats?
- Yes: immediate (new dimension), short term (different materials), medium term (different materials, domains, & format), far (science fair posters, 3 year delay).

Do children have misconceptions about experimental design?
- Several!

Can they be diagnosed?
- Yes, by a very savvy teacher with lots of time per student.

Types of misconceptions about CVS

- Misconception about **Goal** of **our instruction**
  - domain-specific knowledge, rather than domain-general procedure.
- Misconception about **Goal** of **experimentation**:
  - "engineering" approach. Get a big result
- Misconception about **Meaning** of **"fair test"**.
  - "fair" = "same" , so set up ramps so that balls would roll the same distances, rather than trying to FIND OUT about a variable
- Students less willing to ignore prior knowledge, and to **adopt hypothetical stance**.
  - So why bother to control for color of ball?

Lessons learned (continued)

Does learning via "Direct Instruction" transfer to other materials, domains, & test formats?
- Yes: immediate (new dimension), short term (different materials), medium term (different materials, domains, & format), far (science fair posters, 3 year delay).

Do children have misconceptions about experimental design?
- Several

Can they be diagnosed?
- Yes, by a very savvy teacher with lots of time per student.

Can children's misconceptions about CVS be remediated?
- Yes, by a very savvy teacher with lots of time per student.

Are such science teachers easy to find?
- No

What to do?
- Create an intelligent tutor for teaching CVS.

TED Tutor:
Training in Experimental Design

w/ Stephanie Siler, Cressida Magaro, Kevin Willows

Three basic steps for TED construction

1. Determine core "knowledge elements" for expert performance
2. Diagnose current student knowledge
   - Correct
   - Incorrect
3. Provide focused remedial tutoring

Core "knowledge elements" for CVS

In a multi-variable situation, **if** your goal is to determine whether or not a variable plays a causal role in outcome A, **then**

Rule 1: Identify that variable (X) and its values:

Rule 2: Create a contrast:
  a. In Condition 1, Set X to Value 1
  b. In Condition 2, Set X to Value 2

Rule 3: Set all other variables (Y, Z, W) to the same values in both conditions.

"Run" the experiment:
- measure A1 and A2.
- If A1≠ A2, then X is causal.

Hard: variable - variable

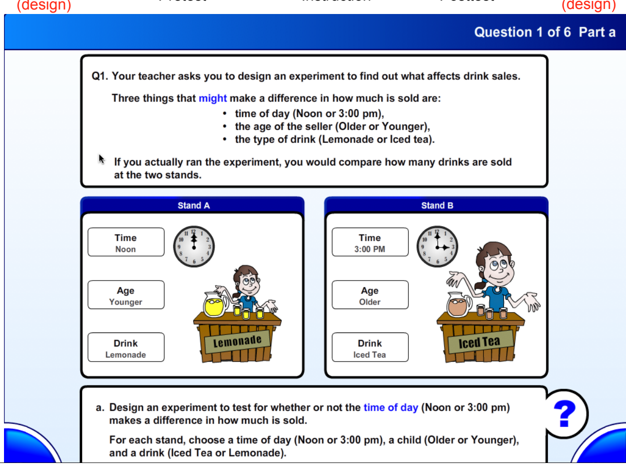
Two empirical studies

- Study 1:
  - How good is a non-adaptive computer TED, presenting "direct instruction"?
    - Compare to science teacher using same materials but via class lecture.
- Study 2:
  - How does non-adaptive TED compare to a good teacher-delivered lesson, using "rich" hands-on materials. (Pittsburgh Public School curriculum)
    - Taken from *Foundations of Physical Science* textbook (Cambridge Physics Outlet - CPO) .

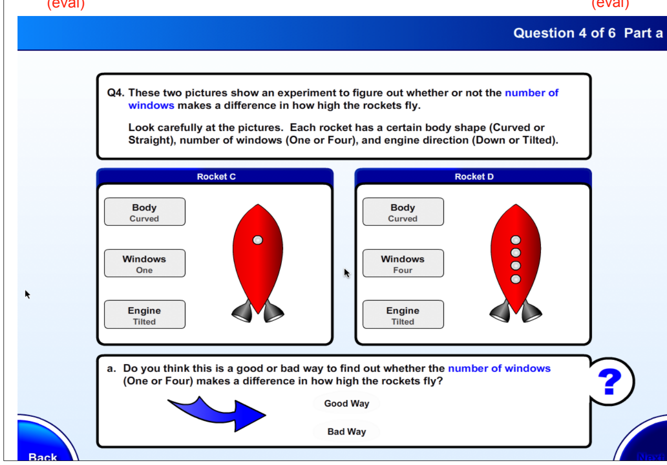
Structure of our assessment studies

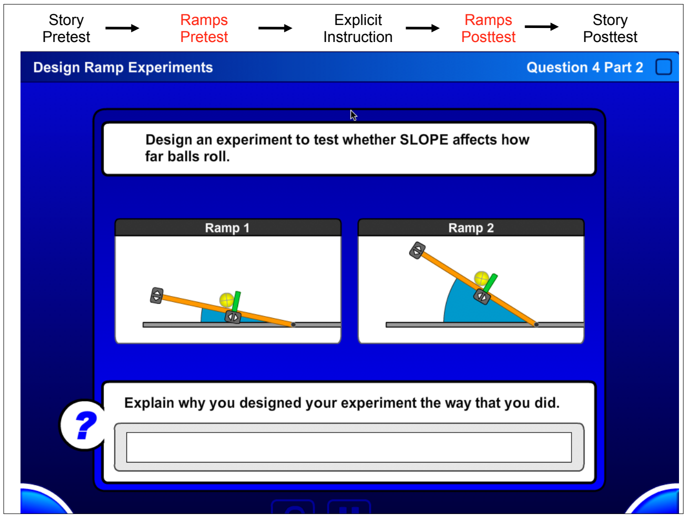
"Story pre" "Ramps Pre" Instruction "Ramps post" "Story post"

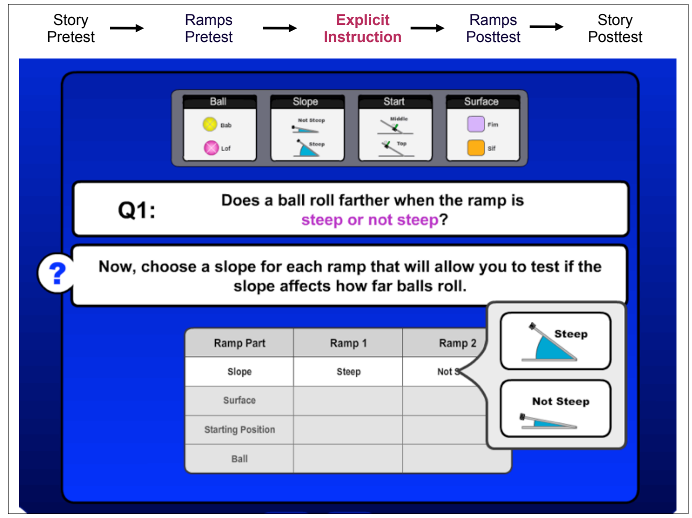
Story Pretest (design) → Ramps Pretest → Explicit Instruction → Ramps Posttest → Story Posttest (design)

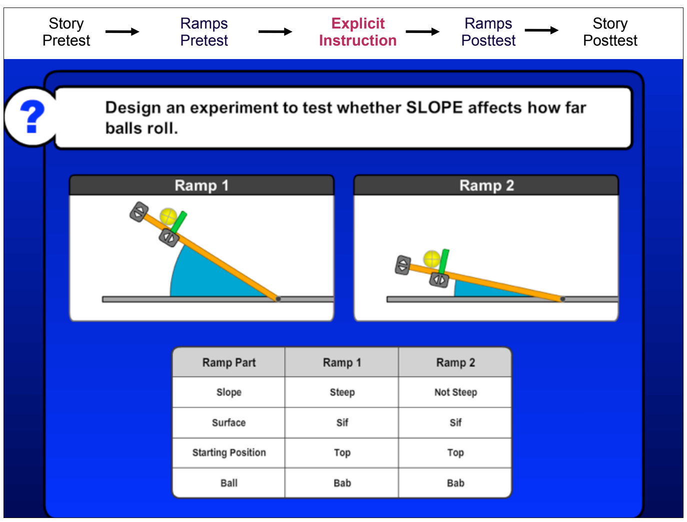


Story Pretest (eval) → Ramps Pretest → Explicit Instruction → Ramps Posttest → Story Posttest (eval)

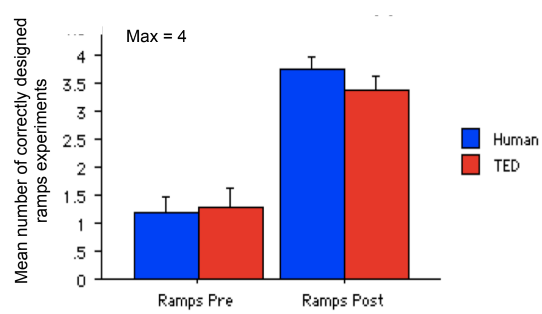








Study 1: TED (non-adaptive) instruction vs. Human instruction on CVS



Students in both conditions showed significant gains in CVS knowledge. No difference in condition.

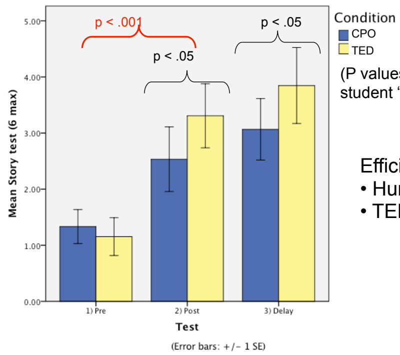
Study 2: Non-Adaptive TED vs Good Science Teacher

- *In vivo*, Pittsburgh Sci Tech Academy
- Two eighth grade classes (N = 29) (70% reduced lunch eligible)
- Design:
  - TED (non-adaptive) (n = 14) vs. Human Science Teacher: (n = 15) between-subjects quasi-experimental:
  - 4th-period = teacher presentation, student gps design and run experiments, class discussion of outcomes
  - 5th-period = TED: individual students using TED interface.
  - Student quality confounded: weaker students in TED condition.

	Experimental Conditions	
	Live teacher & "cool" physical Materials	TED-1: virtual instruction
Ramps Materials	Physical	Virtual
Group activity?	Yes	No
Lesson Intro	Teacher-led (CVS logic)	Video (compare/contrast outcomes)
Main activity	Setting up/running experiment/record results	Evaluating experiments only
IndividualProbes during activity?	No	Yes (consider CVS Logic)
CVS explanations?	No	Yes
Summary	Teacher-led; CVS logic	Video; CVS summary
Final activity	Re-run experiments & discuss results	Ramps "post-test" (no feedback)

“Story Problem” Post-Test Scores: TED tutor vs. Teacher

(max = 6)



(P values after ANCOVA: Factoring out student “general ability”)

Efficiency:
- Human teacher ~100 min
- TED ~60 min

Summary

1. Experimental design is a fundamental domain-general topic in early science instruction.

2. Children have a variety of implicit notions (“pre-conceptions) of what experimentation is about
   - Often incorrect
   - Can be assessed by carefully designed probes
   - Can be remediated by a good (human) tutor

3. Creation of an adaptive instructional system capable of “good tutoring” is feasible, and has thus far been successful.

Supporting Early STEM Learning with Spatial Analogy and Language

Dedre Gentner

Susan Goldin-Meadow
Susan Levine
Nora Newcombe
David Uttal

Supporting spatial learning and STEM achievement: from lab to world

Spatial language

Spatial analogy

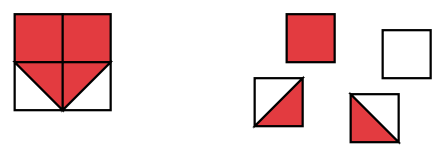
Combining spatial language and spatial analogy to promote learning

Spatial language is important in spatial learning

Early production of spatial language (14-46 mo) predicts later performance on spatial tasks (54 mo)

(Pruden, Levine & Huttenlocher, under review; Levine et al., under review)

e.g., Block Task



Knowledge of specific spatial terms predicts performance on spatial tasks

(Dessalegn & Landau, 2008; Haun et al., 2006; Hermer-Vazquez et al., 1999, 2001; Loewenstein & Gentner, 2005)

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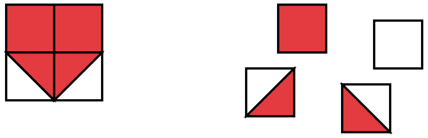


Knowledge of specific spatial terms predicts performance on spatial tasks

(Dessalegn & Landau, 2008; Haun et al., 2006; Hermer-Vazquez et al., 1999, 2001; Loewenstein & Gentner, 2005)

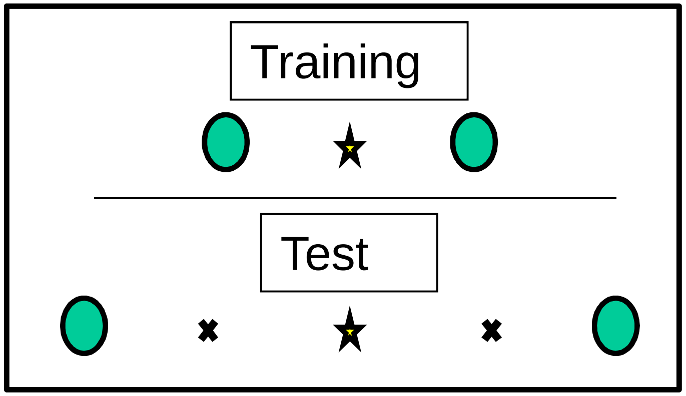
But is this a causal relation?

Spatial language and spatial cognition: The midpoint relation

- The midpoint relation is important in STEM disciplines
  - *Balance*, *bisection, half*
  - *Proportion, scale*

- The midpoint relation is a complex spatial relation
  - Requires locating a figure relative to two reference objects

- Non-human animals have difficulty encoding the midpoint
  - **gerbils** (Collett, Cartwright, & Smith, 1984)



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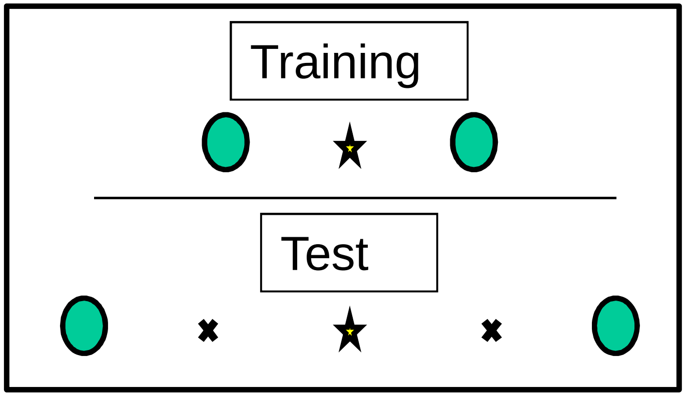
  - **gerbils** (Collett, Cartwright, & Smith, 1984)

- 4-5-year-old humans can succeed
  (Uttal, Sandstrom & Newcombe)



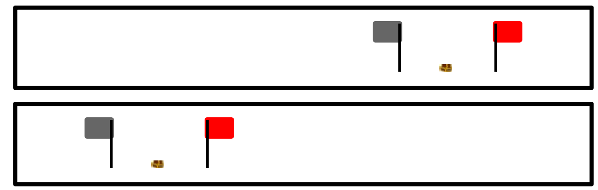
Does spatial language help children grasp the midpoint relation?

Midpoint task
(with Nina Simms)

2 ½- to 5-year-olds

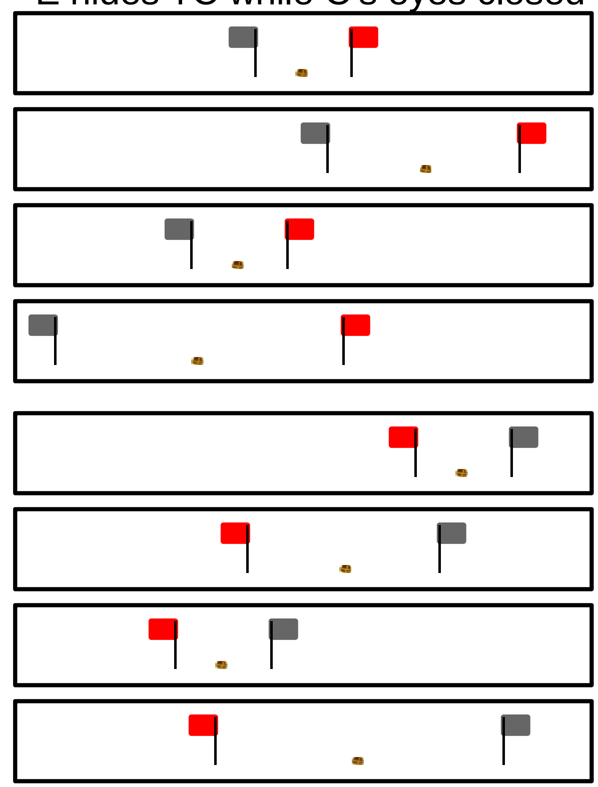
Training

C watches E hide TC



Test

E hides TC while C's eyes closed



Middle and the Midpoint Task

Simms & Gentner, 2008, in prep.

Results:

- Many mistakes among younger children
- Children who did well on the Midpoint Task also did well on a post-test of spatial language—specifically, *middle* and *between*

But is there a causal link from using *middle* to facility with the midpoint relation?

Study 2: Vary whether children hear *middle* during the Midpoint Task

Does spatial language help children grasp the midpoint relation?

Study 2 (ongoing): Vary whether children hear spatial language (*middle*) or not during first 4 trials of Midpoint Task

Label:

“The treasure chest is in the middle of the two flags”

No Label

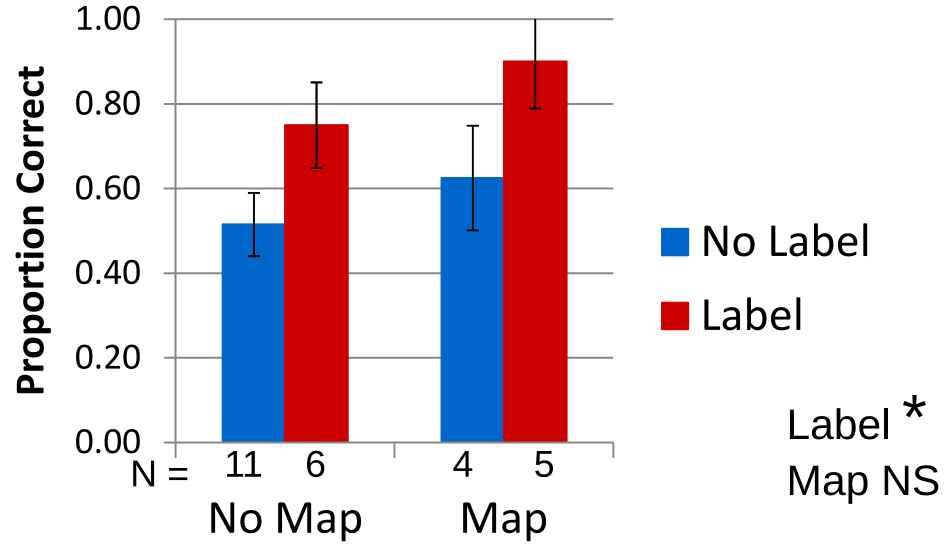
1st half of Midpoint Task

Removed for 2nd half

Study 2 (ongoing) – Hearing the term *middle* improves performance on the Midpoint Task

During Manipulation

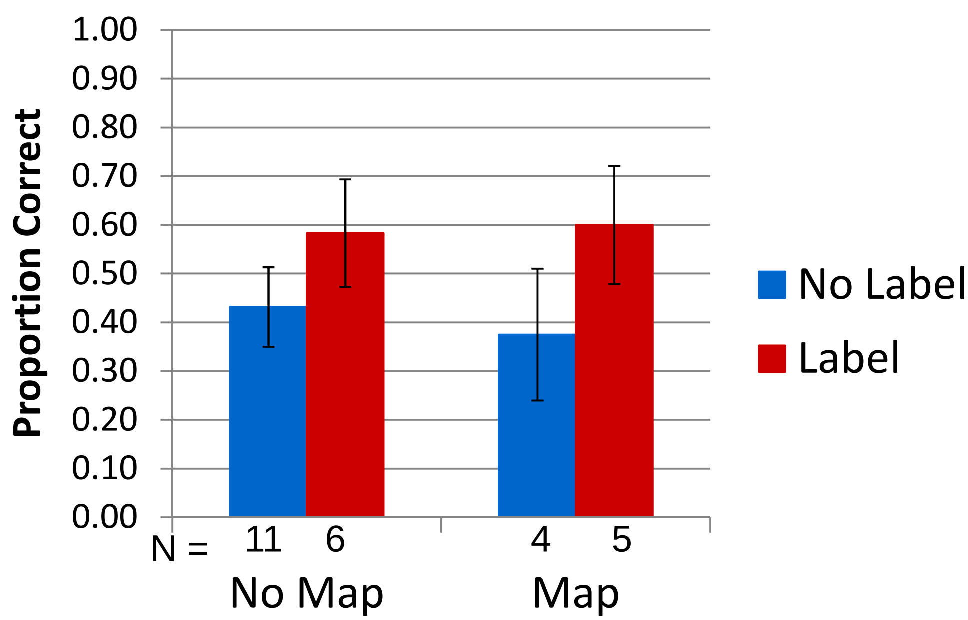
3½-year-olds do better if they hear the term *middle* on each trial



No effect for maps

After Manipulation

This advantage appears to persist after the term is no longer used



Supporting spatial learning

Spatial language

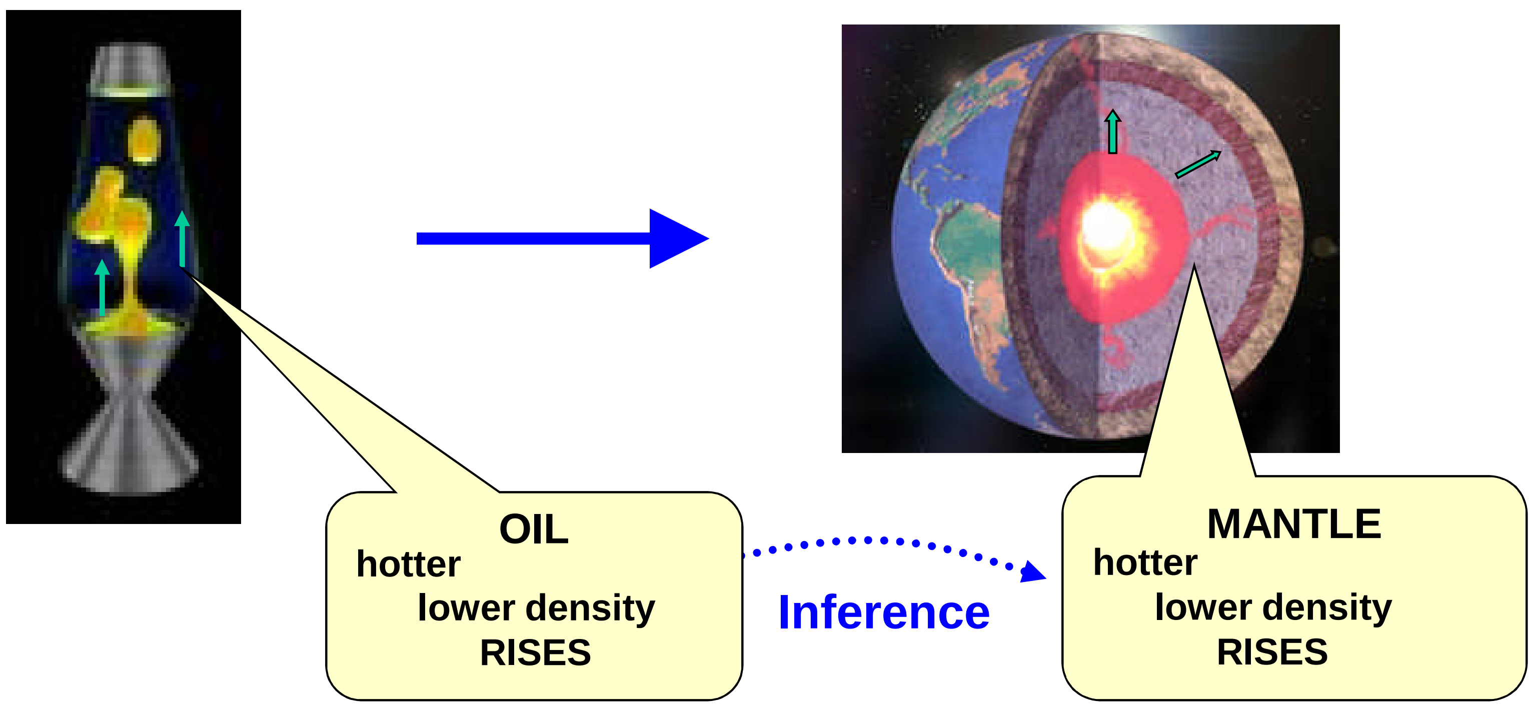
Naming spatial concepts and relations promotes comparing and categorizing across exemplars

and helps learners preserve and transfer spatial concepts

Spatial analogy

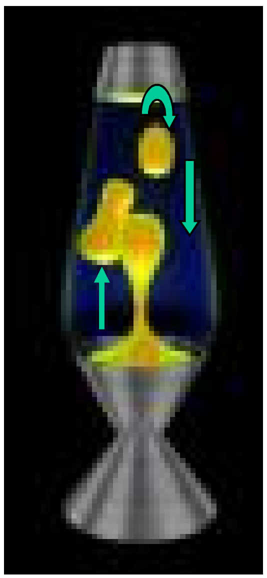
Combing spatial language and spatial analogy

Analogy fosters STEM learning:
Importing spatial knowledge from familiar to unfamiliar domains



Jee et al., 2009; Kastens & Rivet, 2010; Sibley, 2009

Analogy fosters STEM learning:
Abstracting common spatial systems from two different domains

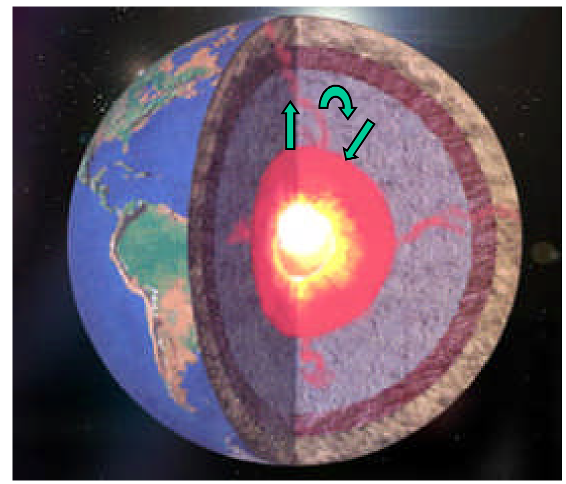


ABOVE

cools
contracts
higher density
SINKS

BELOW

heats up
expands
lower density
RISES

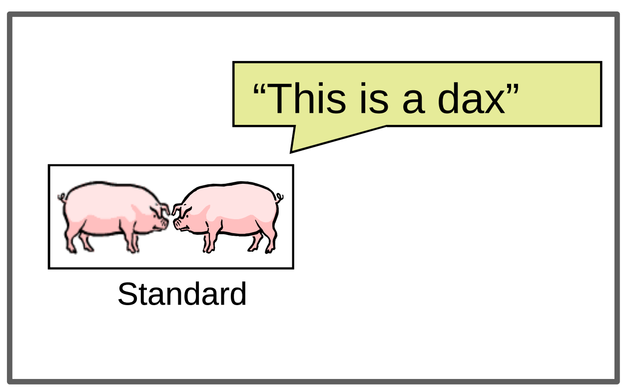


Spatial analogy supports learning spatial concepts, even in very young children

- Teach 3- and 4-year-olds novel spatial relational configurations

(Christie & Gentner, 2010)

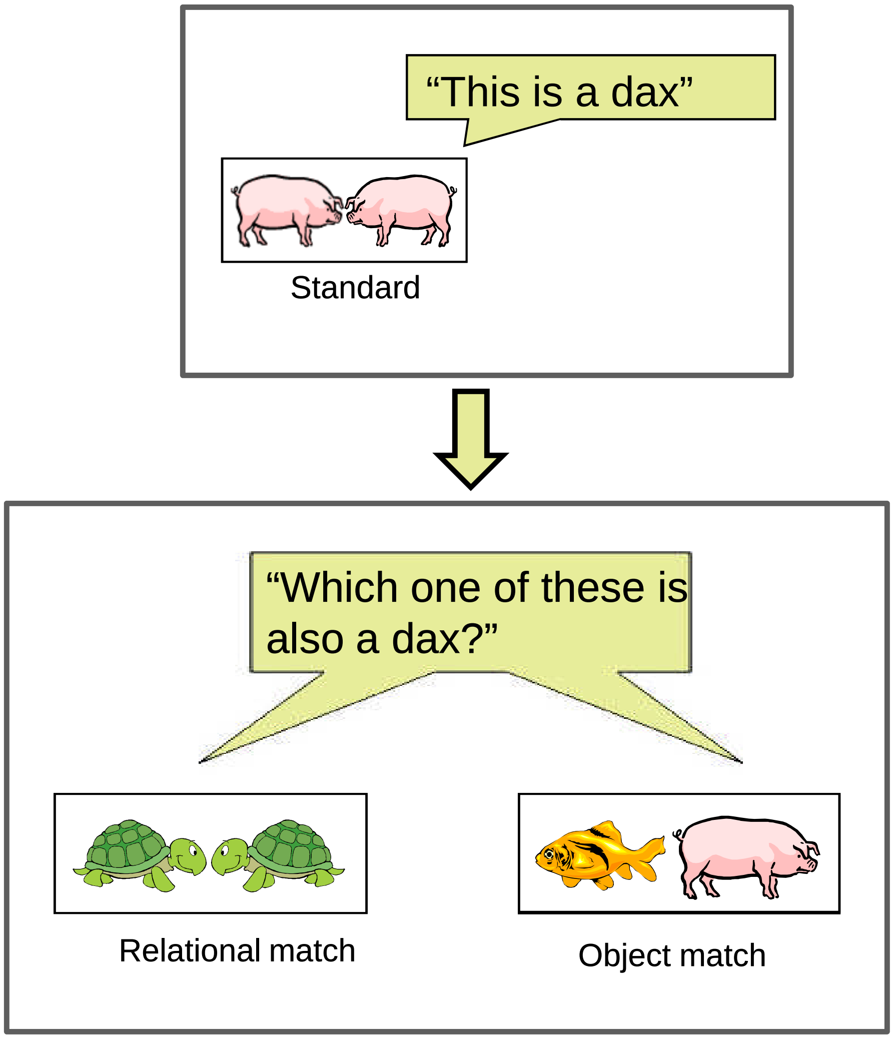
- Test whether spatial alignment can promote attention to common spatial relations



Learning spatial concepts

(Christie & Gentner, *Journal of Cognitive Development* 2010)

Word-learning task



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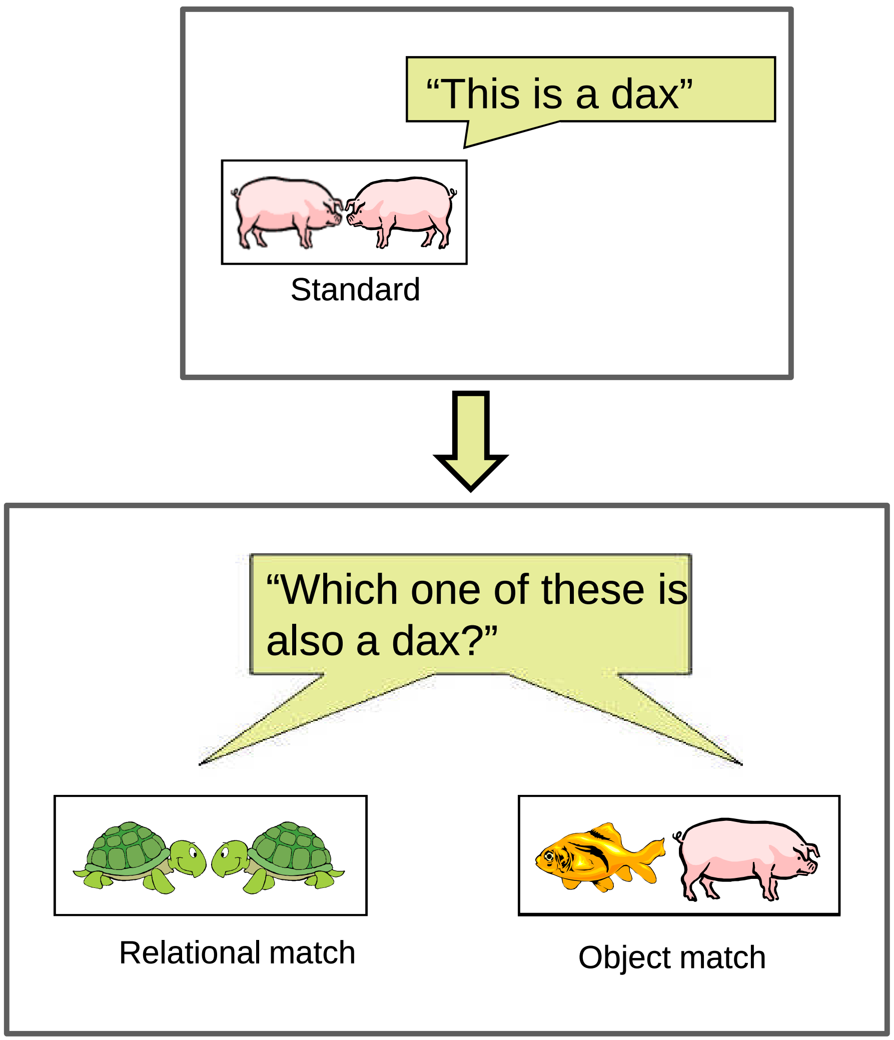
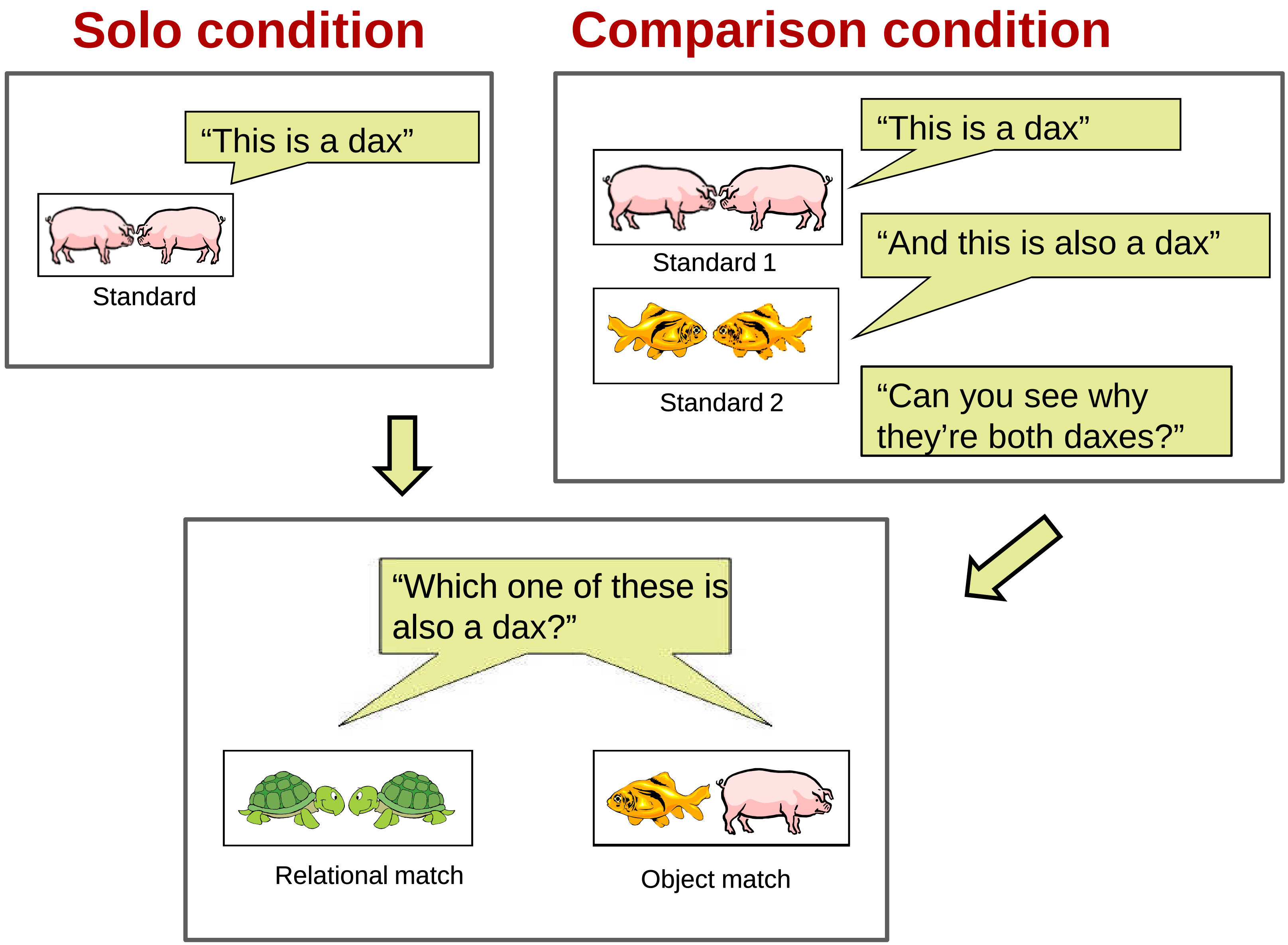


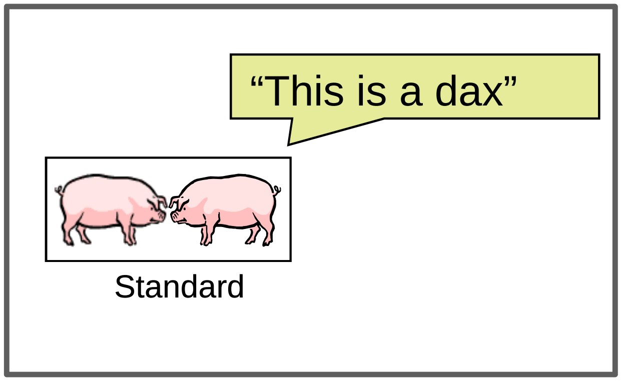
3-year olds:
98% object match

Comparison promotes learning spatial concepts

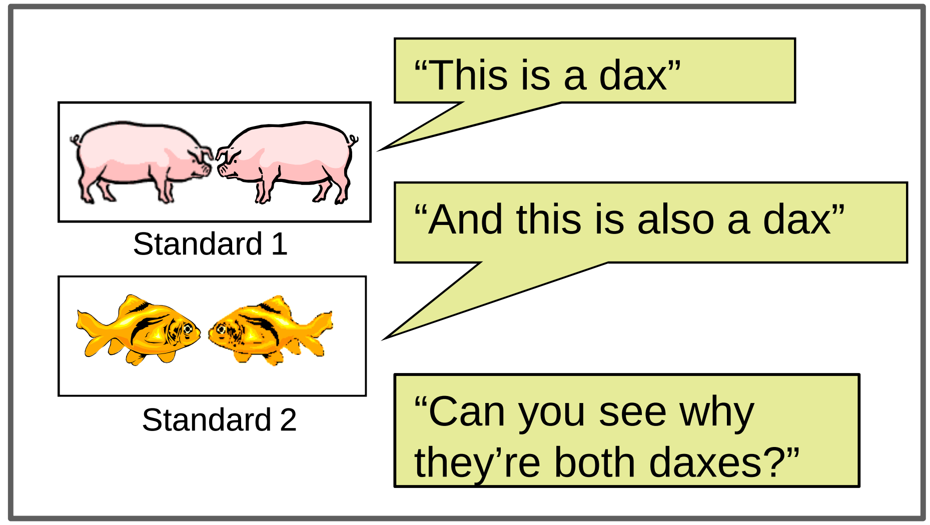


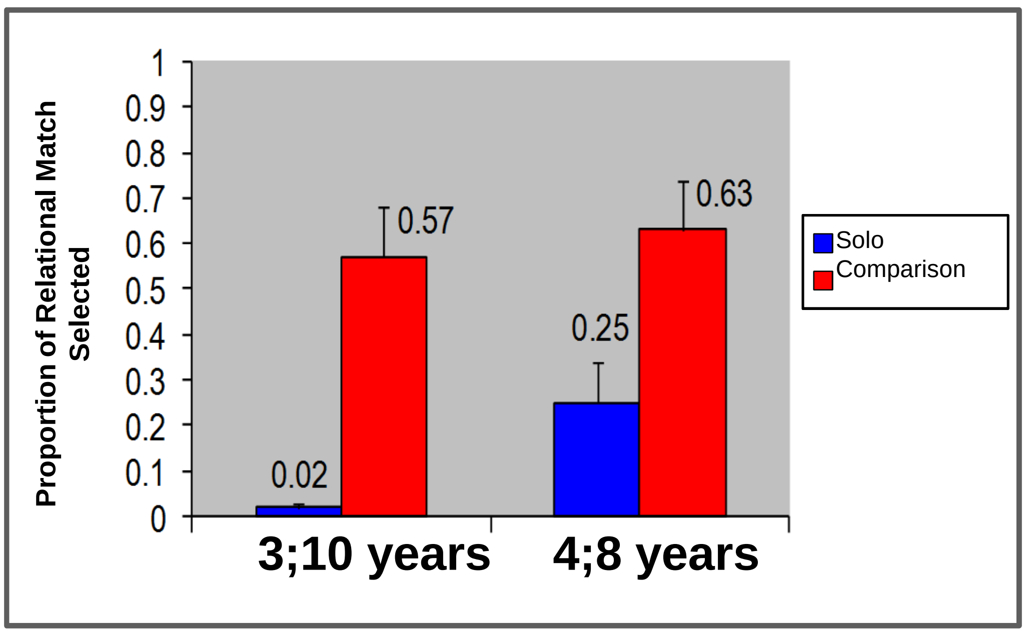
Comparison promotes learning spatial concepts

Solo condition



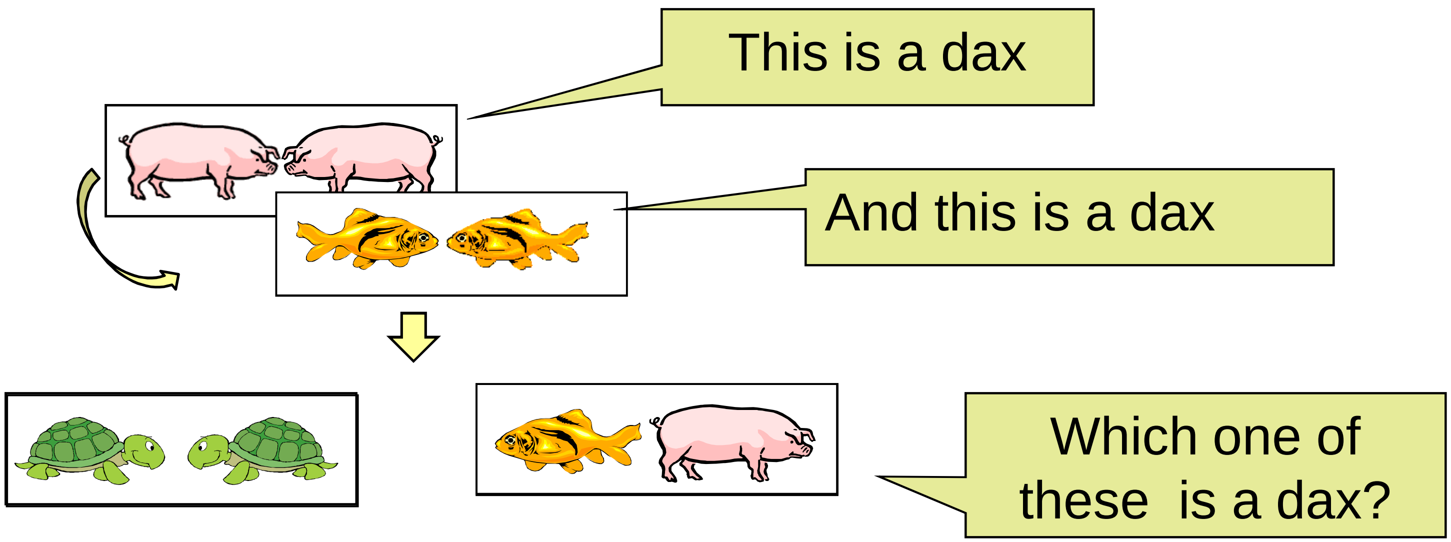
Comparison condition





Comparison is the key

- Second study found that sequential presentation was no better than solo presentation (Christie & Gentner, 2010)
- Comparison—structural alignment—is the essential ingredient. Just having two exemplars is not enough



From lab to museum: Using comparison to help children learn a basic engineering principle

Research at the Chicago Children's Museum

(Gentner, Levine, Dhillon, & Poltermann, 2009; in preparation)

Child builds a skyscraper with family

- **Free-form construction**
- **Children often fail**

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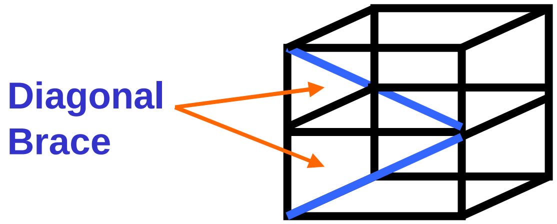
Child builds a skyscraper with family

Free-form construction

Children often fail

Our goal: Teach children that triangles/diagonals confer stability



Using spatial analogy to teach about engineering

(Gentner, Levine, Dhillon, & Poltermann, 2009)

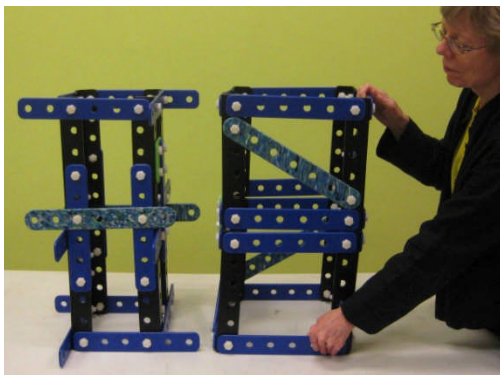
2-minute training task

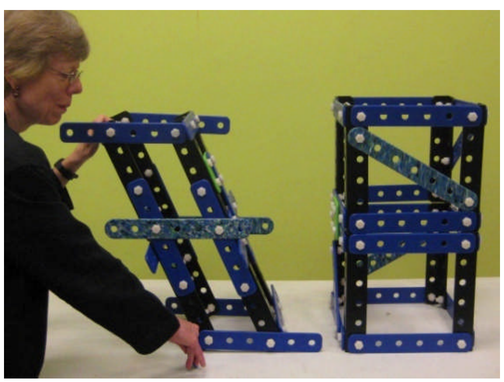
Three groups:
- High-alignable comparison
- Low-alignable comparison
- No training

Low Alignability

Training

High Alignability





"Which one do you think is stronger?"

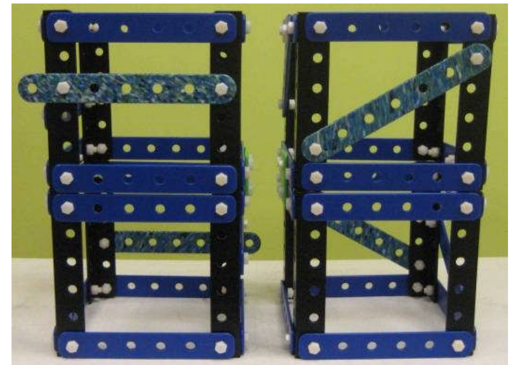
[Child guesses]

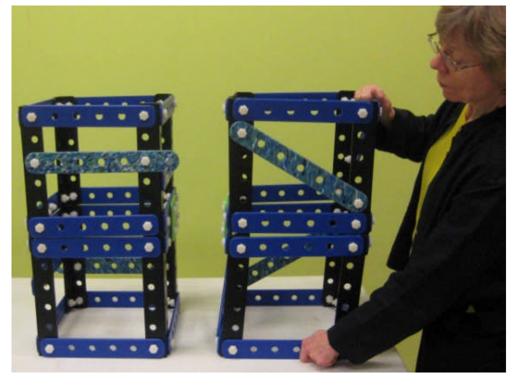
"OK, now see if you can wiggle them"

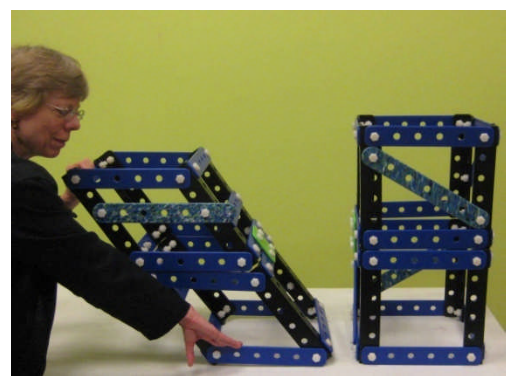
[The building with the diagonal does not bend.]

"Now which do you think is stronger?

Yes, this one is strong! It doesn't wobble because it is stable". "







Result: Spatial alignment helps children learn about *bracing*—a key elementary engineering principle

- After training, children construct skyscraper with family
- Then they get **repair task:**

"This building is wobbly. Can you show me where to put this piece to make it strong?"

Result: Spatial alignment helps children learn about *bracing*—a key elementary engineering principle

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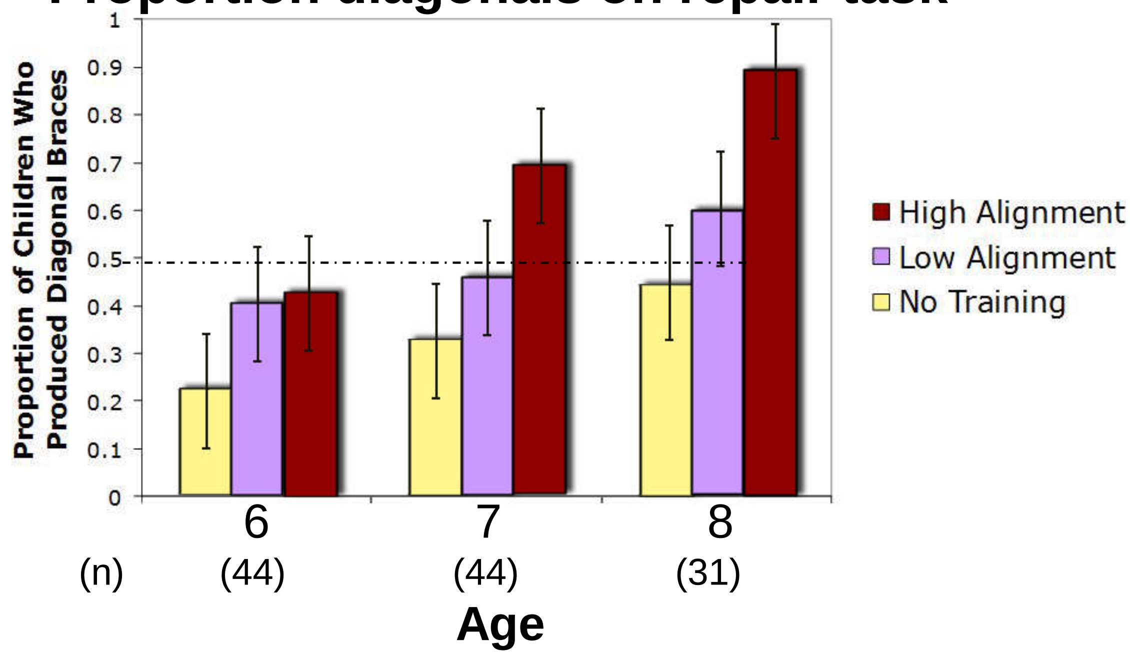
- Then they get **repair task:**

"This building is wobbly. Can you show me where to put this piece to make it strong?"

Proportion diagonals on repair task

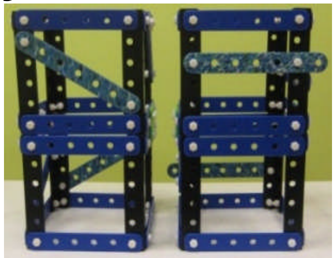


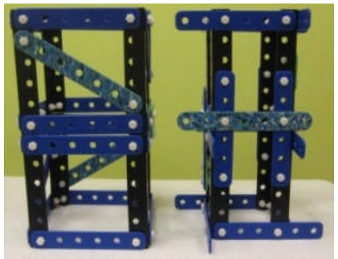
Lab Study: Combining spatial language with spatial alignment to facilitate transfer

(with Micah Goldwater)

Phase 1: Replicate Children's Museum Study

- High Alignability vs. Low Alignability
- Repair task
- **Result: High align > Low align**





Phase 2: Label

- Language (*Brace*) vs. Control

Phase 3: Transfer to Novel Structures

Overall Design: 2x2

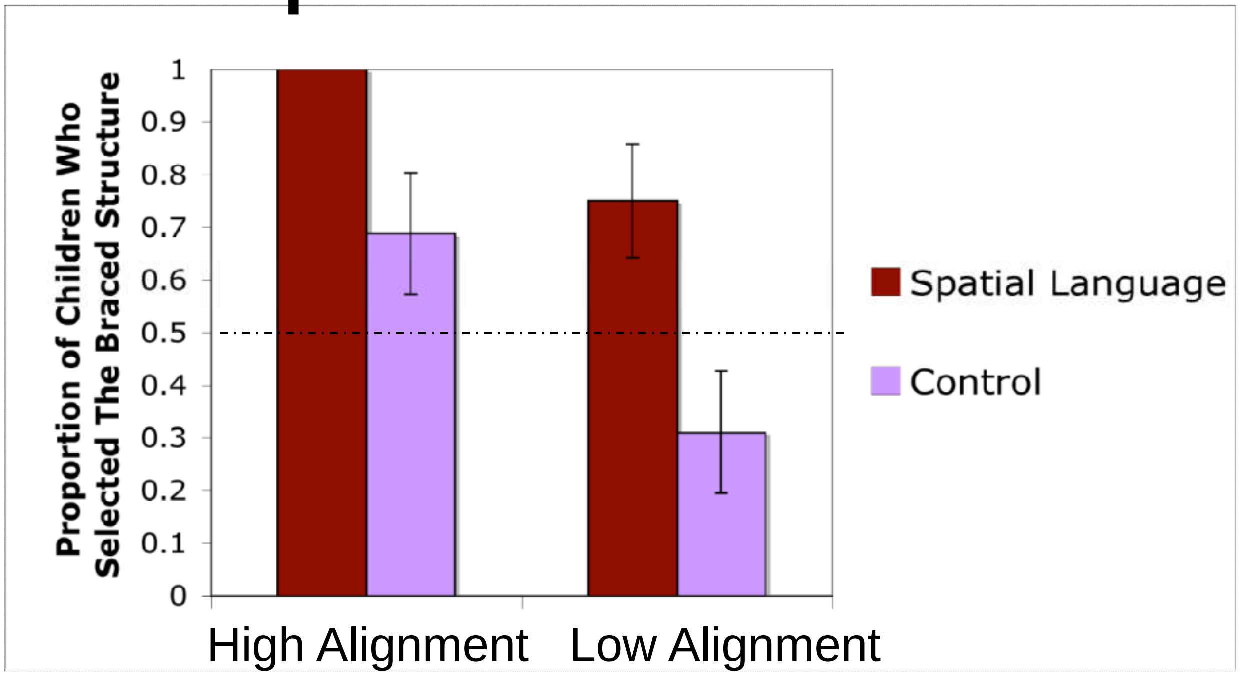
- Alignability (High vs. Low)
- Language (Label vs. Control)

Age: 5;6 – 7;4 (M = 6;5)

Spatial language combines with spatial alignment to foster transfer

Transfer Test: "Which one is stronger?"

Proportion correct choices



(n = 32) (n = 32)

Age: 5;6 – 7;4

100% of children given High Alignment + Spatial Relational Language succeed!

Museum of Science and Industry: Bridge-building

(Applebaum, Spaepen, Gentner, Levine, & Goldin-Meadow)

- 4th through 6th grade classes
- Instructional lab on building stable bridges
- Pre-test → Instruction → Post-test

High-alignment pairs
or Low-alignment pairs

Preliminary results:

- High-alignment group is better at transfer to other structures
- Low SES group especially benefits from highly alignable examples

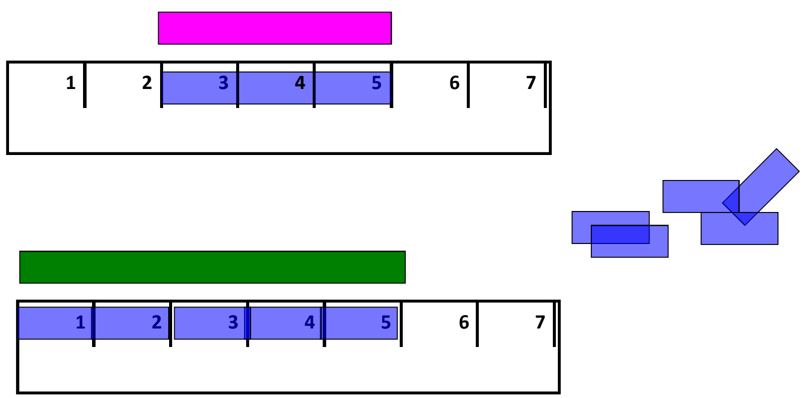
Further projects

Ongoing: Combining spatial language and spatial analogy together to accelerate learning

e.g., graphing stock & flow systems

Teaching measurement in Chicago schools

(Levine, Goldin-Meadow & colleagues)



Summary: Two tools of spatial learning

Spatial analogy **is important in spatial learning**

- **Invites new inferences**
- **Highlights and abstracts key spatial structures**
- **Reveals alignable differences**

Spatial language **is important in spatial learning**

- **Common spatial language invites comparison**
  - **which fosters abstraction of spatial structures**
- **Spatial language preserves spatial abstractions and makes them more portable**

Analogy fosters spatial learning: ***Abstracting spatial principles***

- Spatial analogy promotes
  - highlighting and abstraction of common spatial system
- So spatial relational structure becomes
  - more explicit
  - less contextually embedded
  - more portable in transfer to new contexts
- **These processes promote learning at all stages of development using spatial language**

Sketch Understanding: From laboratory to classroom and back

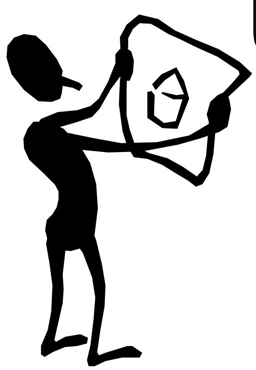
Kenneth D. Forbus
Northwestern University

SILC

Computer tutors and learning environments need spatial capabilities

- Intelligent tutoring systems are providing valuable benefits in some STEM areas
- But not in spatially rich subjects (e.g. geoscience, engineering)
  - Modeling human visual, spatial, & conceptual understanding involves hard scientific questions
- Sketch understanding software could change this

Ultimate goal:
Software that
understands sketches
as you would



Requires Center-level
cross-discipline effort

CogSketch Research Goals

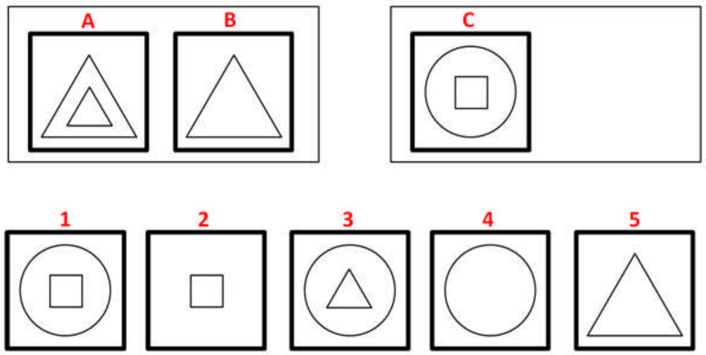
- Goal: A cognitive science research instrument.
  - A computational model of spatial reasoning and learning
  - A tool for gathering data in laboratory and classroom studies
- Goal: A platform for sketch-based intelligent educational software
  - Worksheet model
  - Helping students learn engineering design
- **Vision: Sketch understanding software to help students learn could be widely available within 6 years**

SILC

Some CogSketch Simulation Examples

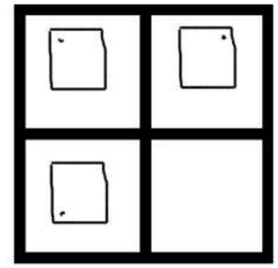
Geometric Analogy

- Problems of the form "A is to B as C is to __?"

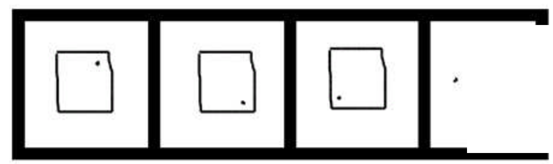


Made reaction time prediction subsequently confirmed via behavioral experiment

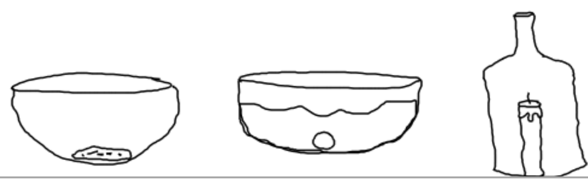
Raven's Progressive Matrices



- Used to measure intelligence
- Extensive data on human performance available



Learning spatial prepositions

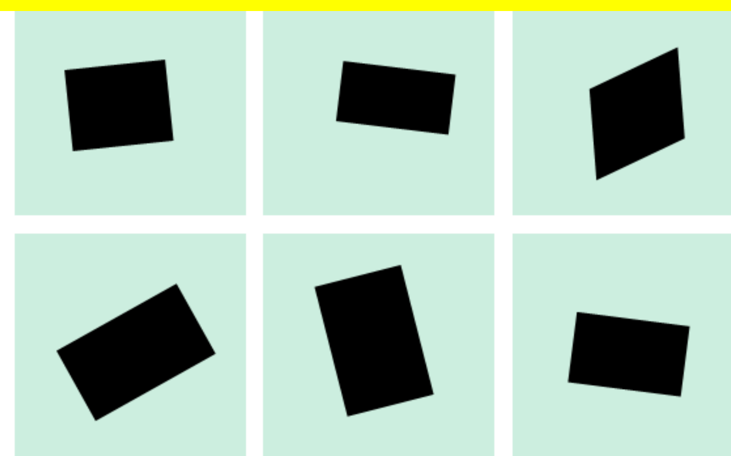


Best Generalization IN
Size: 3
(*candle in bottle, cookie in bowl, marble in water*)
--DEFINITE FACTS:
(rcc8-TPP figure ground)
--POSSIBLE FACTS:
33% (Basin ground)
33% (Bowl-Generic ground)

English & Dutch, with orders of magnitude less data than previous models

Visual Oddity Task

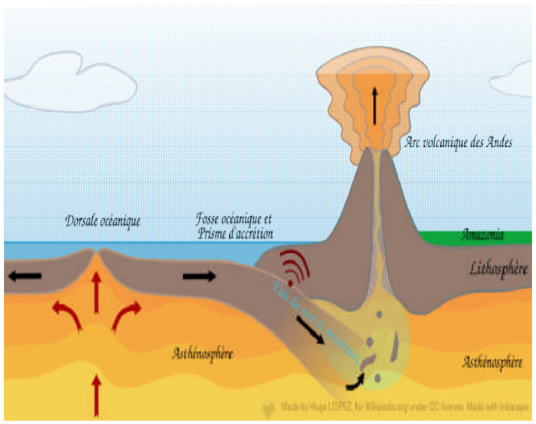
Captures relative difficulty, Δs between Americans and Munduruku

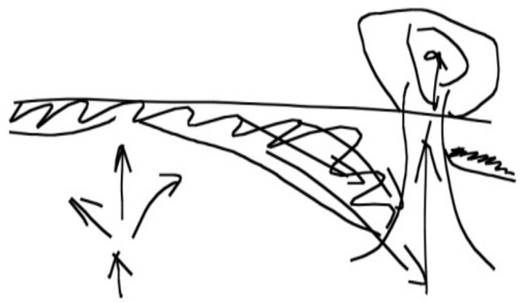


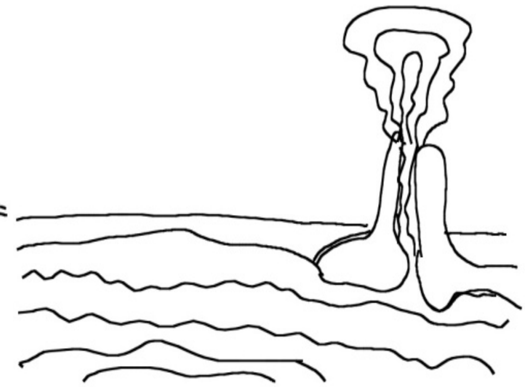
Examples of CogSketch lab experiments

Jee, et al. Drawing on Experience: Use of sketching to evaluate knowledge of spatial scientific concepts (CogSci 2009)

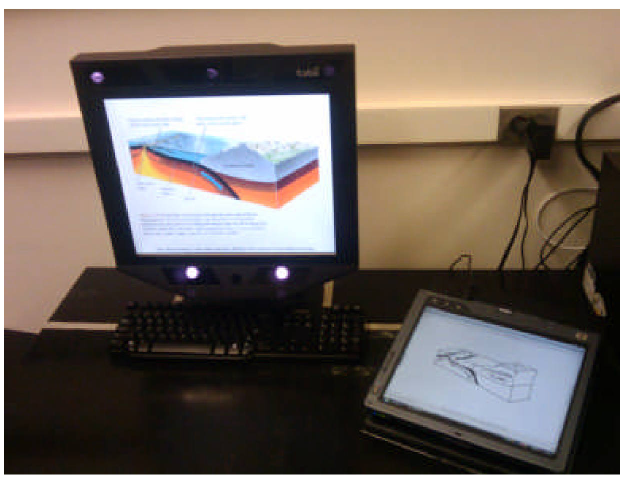
Causal/cycle diagram **Geo student sketch** **Novice sketch**



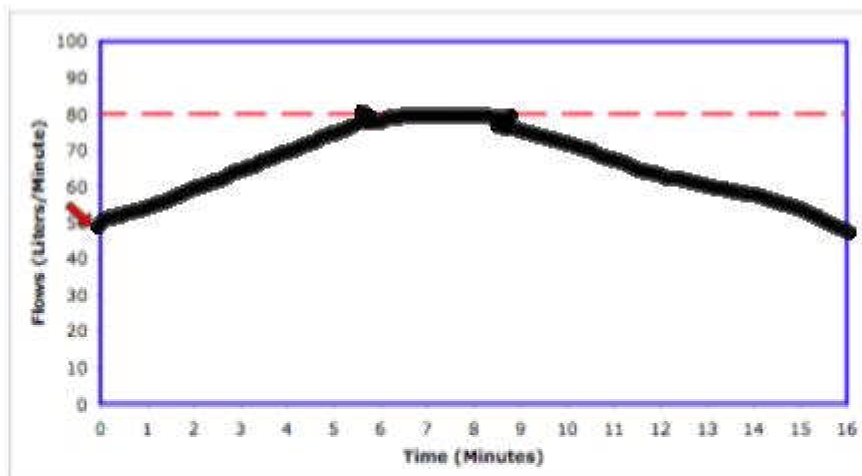




Glazek & Shipley, Temple U.



Smith & Gentner, Northwestern U



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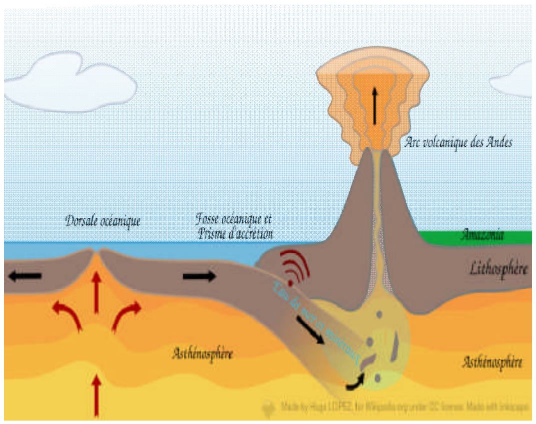
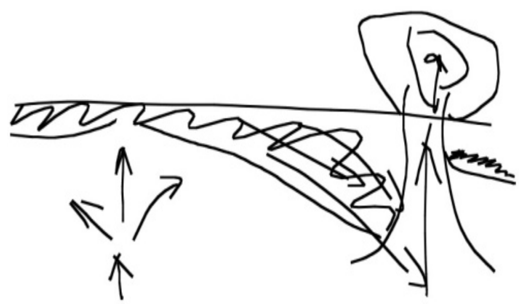
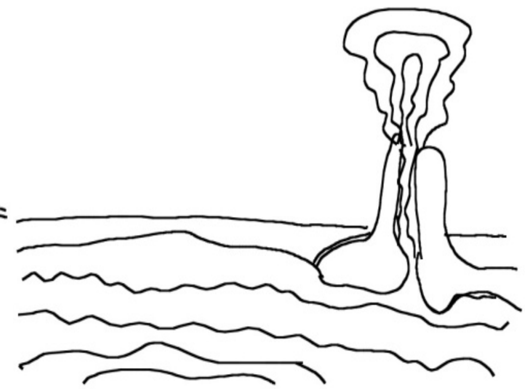
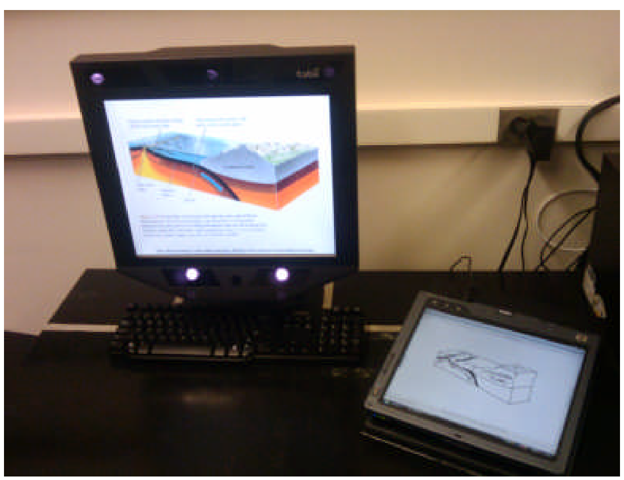


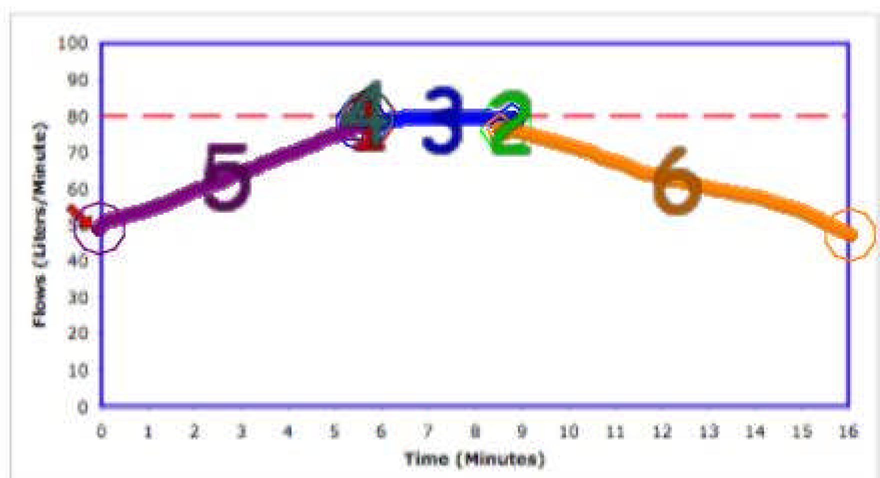




Glazek & Shipley, Temple U.

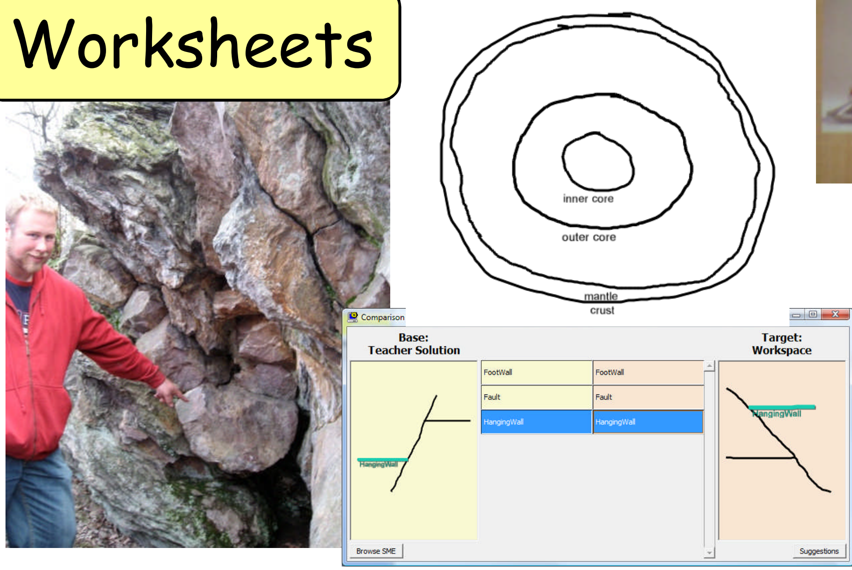


Smith & Gentner, Northwestern U

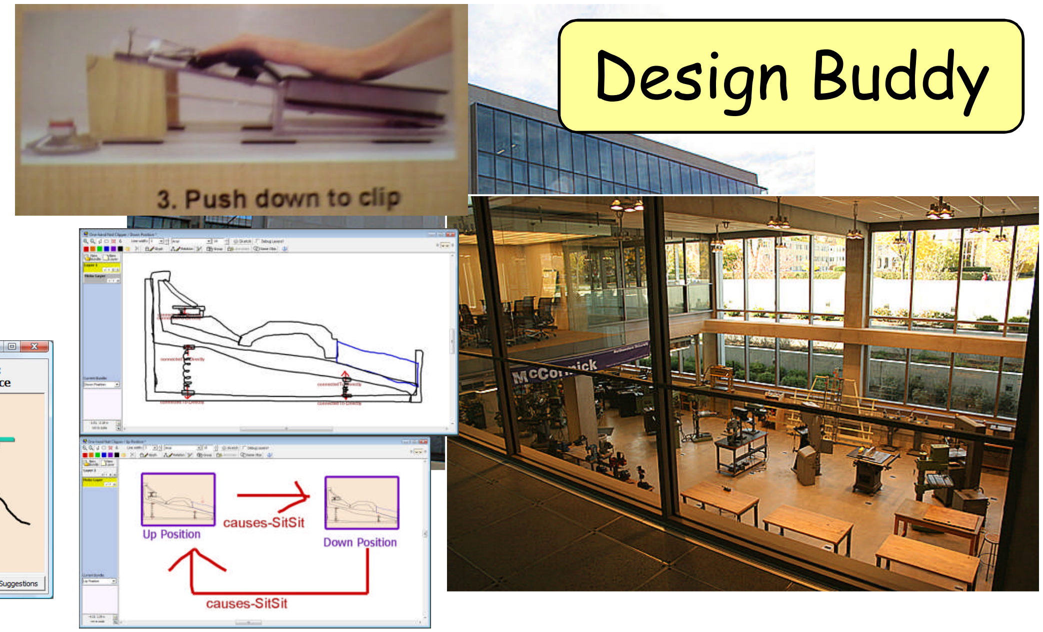


CogSketch Education Projects

Worksheets



Design Buddy

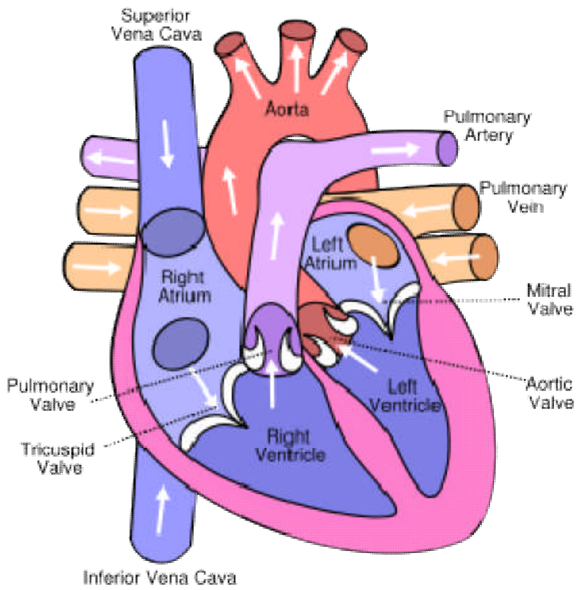


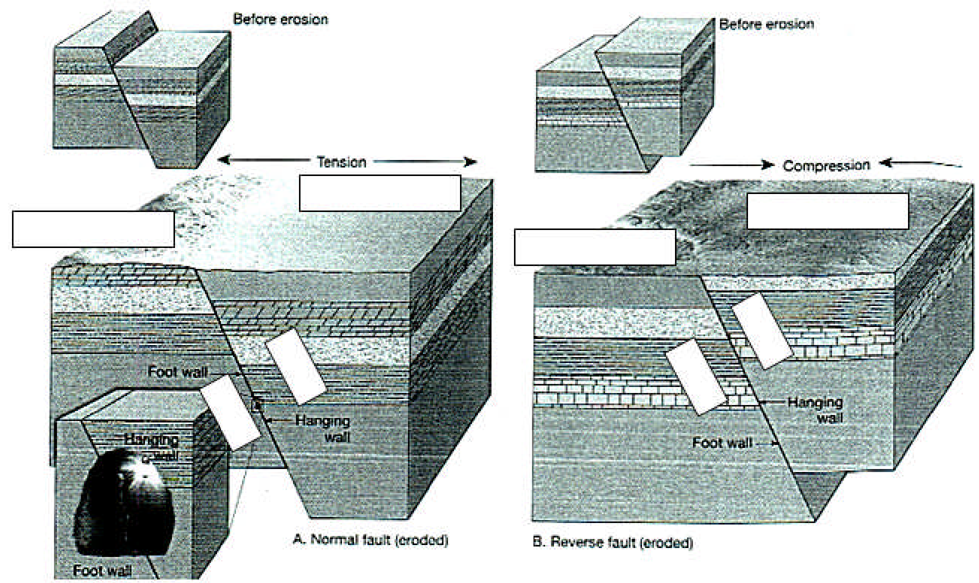
- <u>Problem</u>: Students must understand spatial layouts and terminology
- *Sketch worksheets* scaffold and assess students in sketching exercises
- Lead student: Maria Chang

- <u>Problem</u>: Students have trouble using sketches to communicate their ideas
- *Design Buddy* provides feedback on student explanations
- Lead student: Jon Wetzel

Motivation for Sketch Worksheets

Paper-based worksheets are a staple in many classrooms.

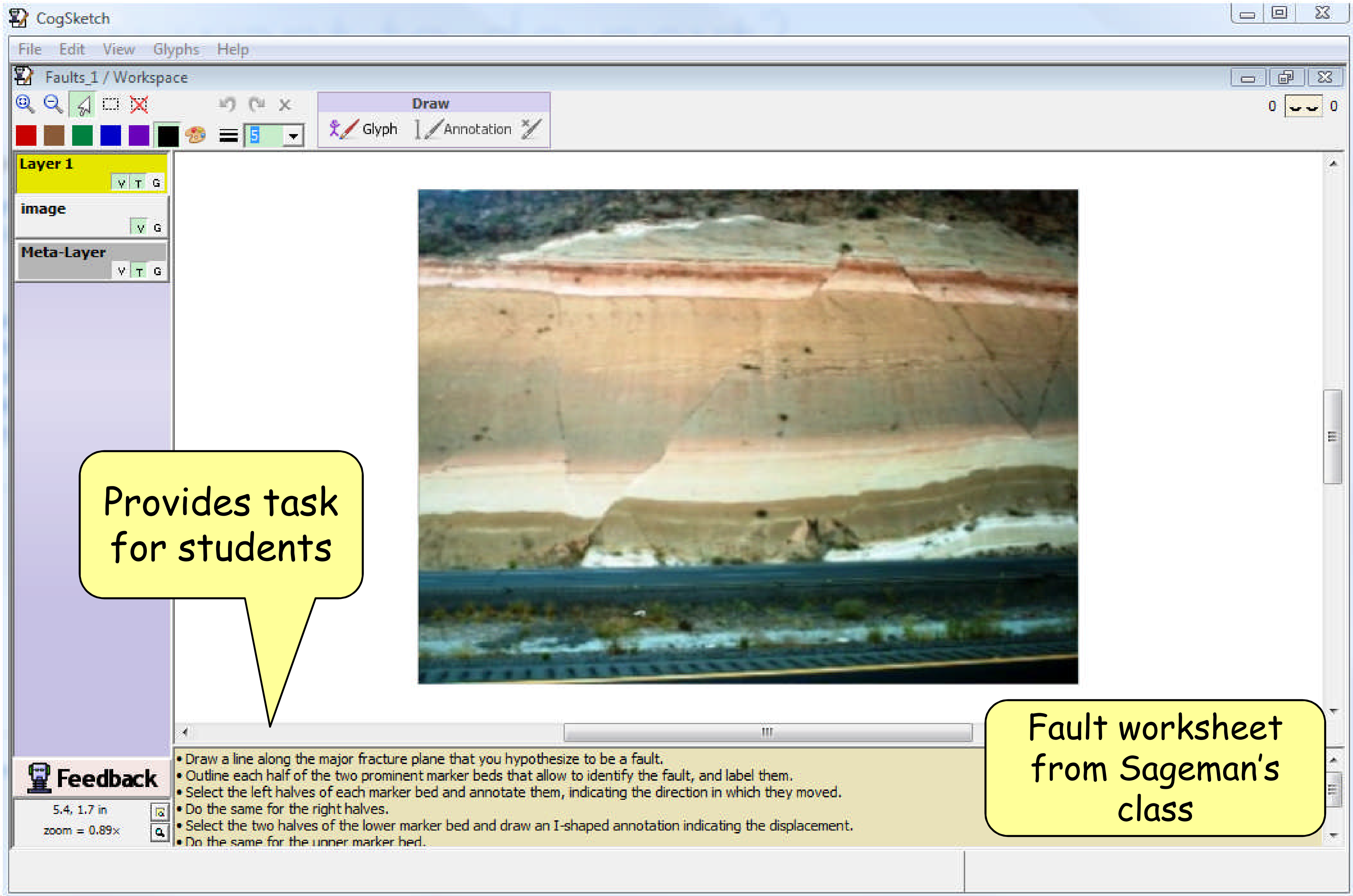




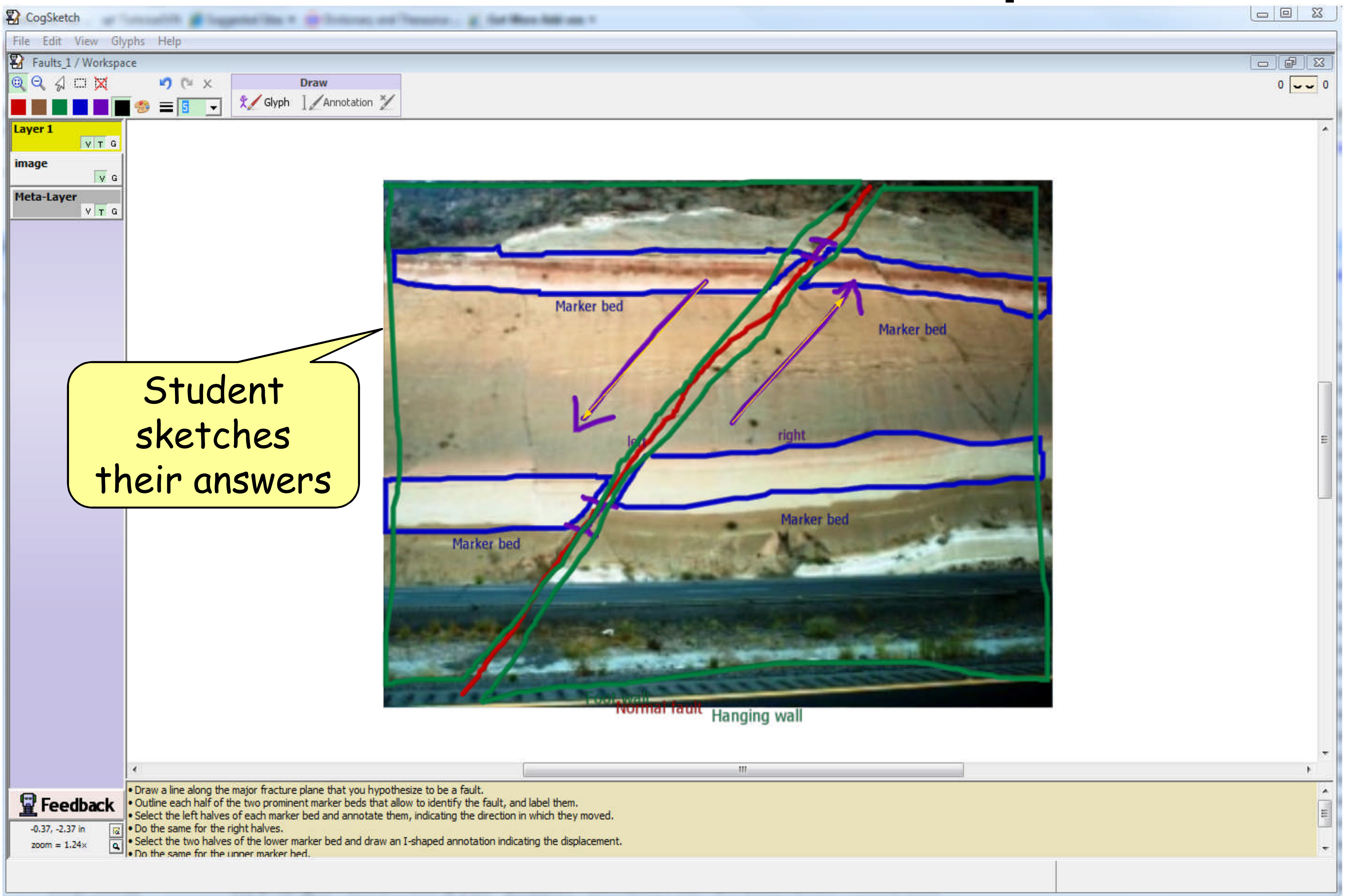
- Sketching is a valuable way of learning spatial relationships. ✓
- Feedback on pencil and paper worksheets is delayed. ✗
- Grading paper-based worksheets is time-consuming. ✗

SILC

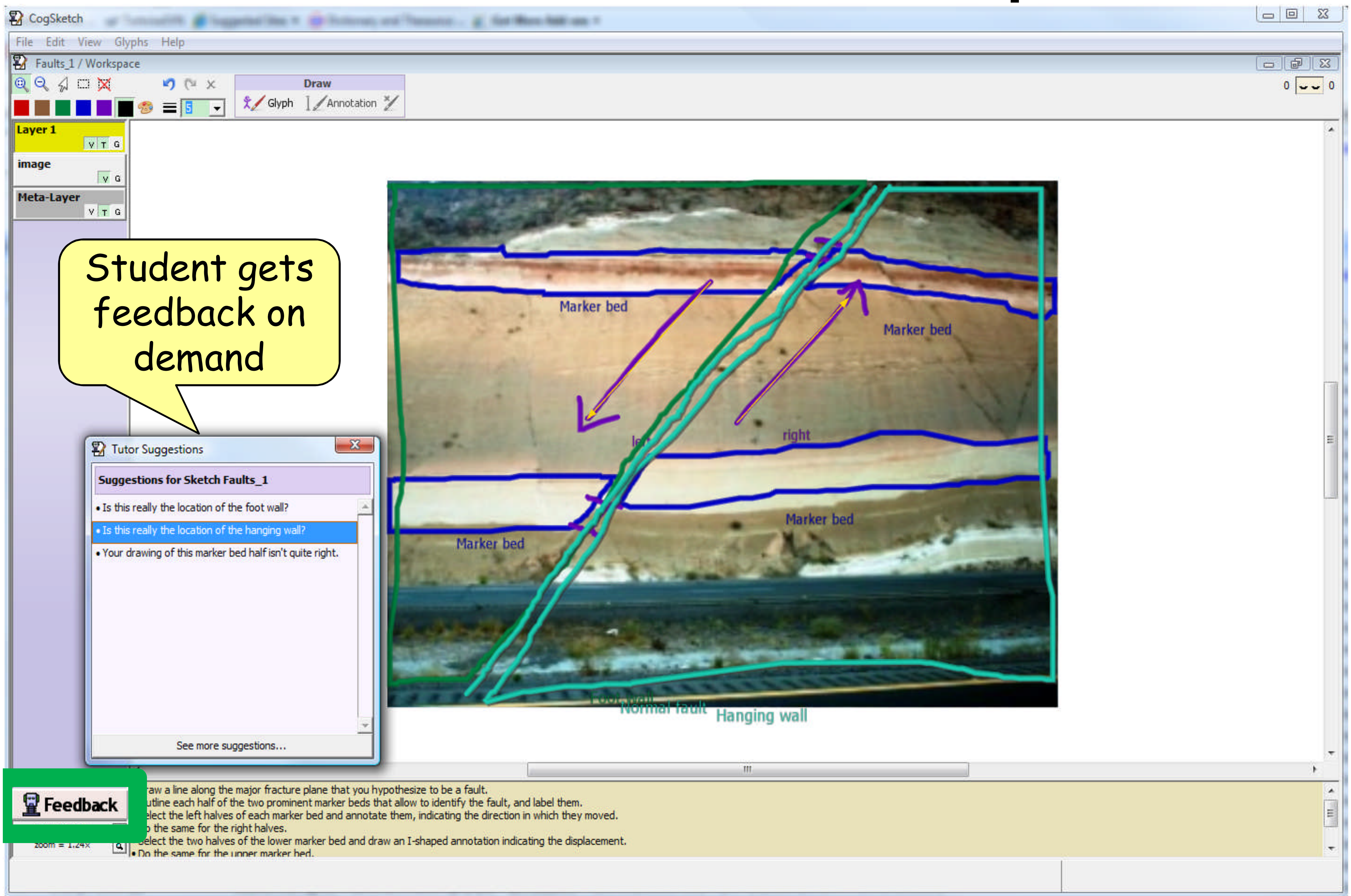
Sketch Worksheets: Example



Sketch Worksheets: Example

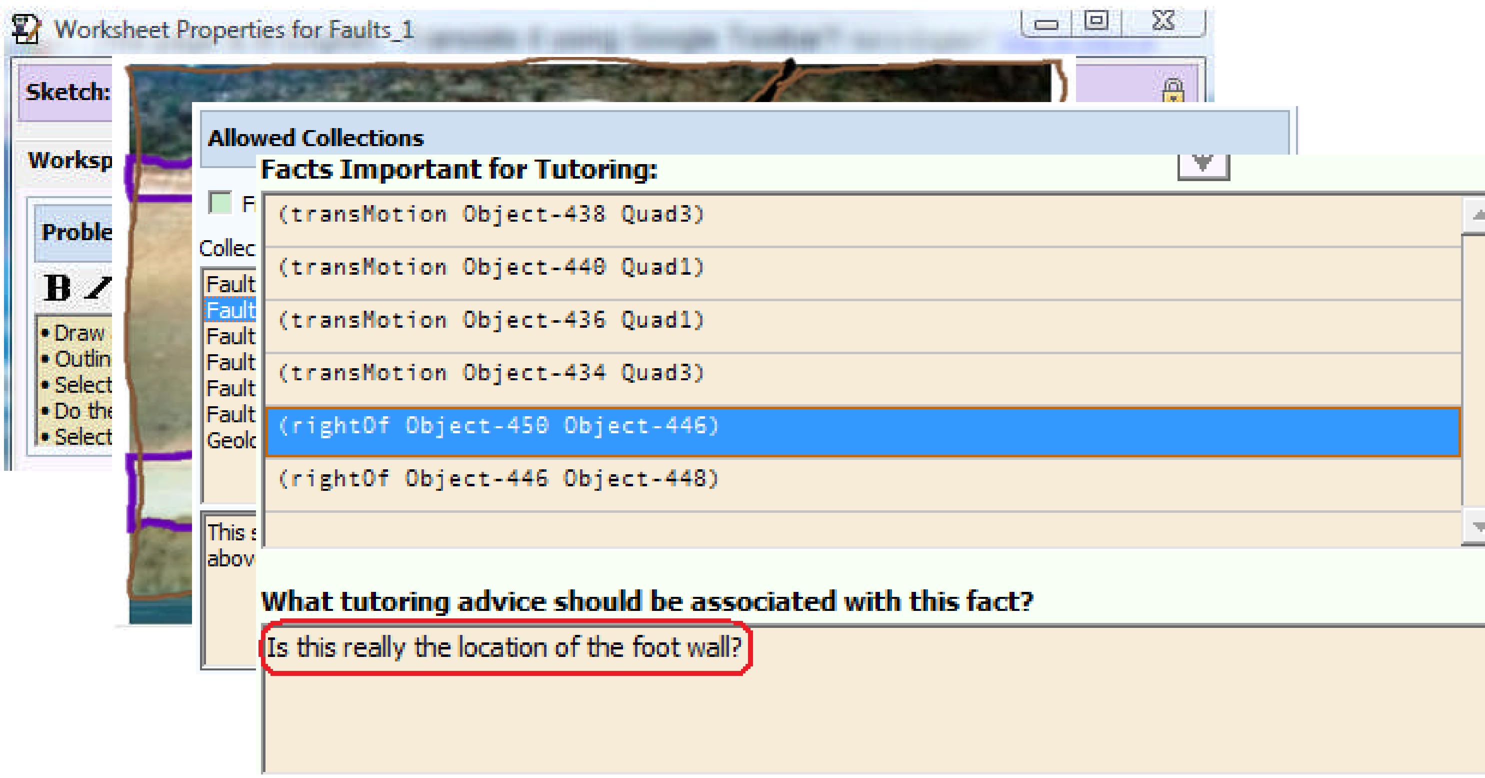


Sketch Worksheets: Example



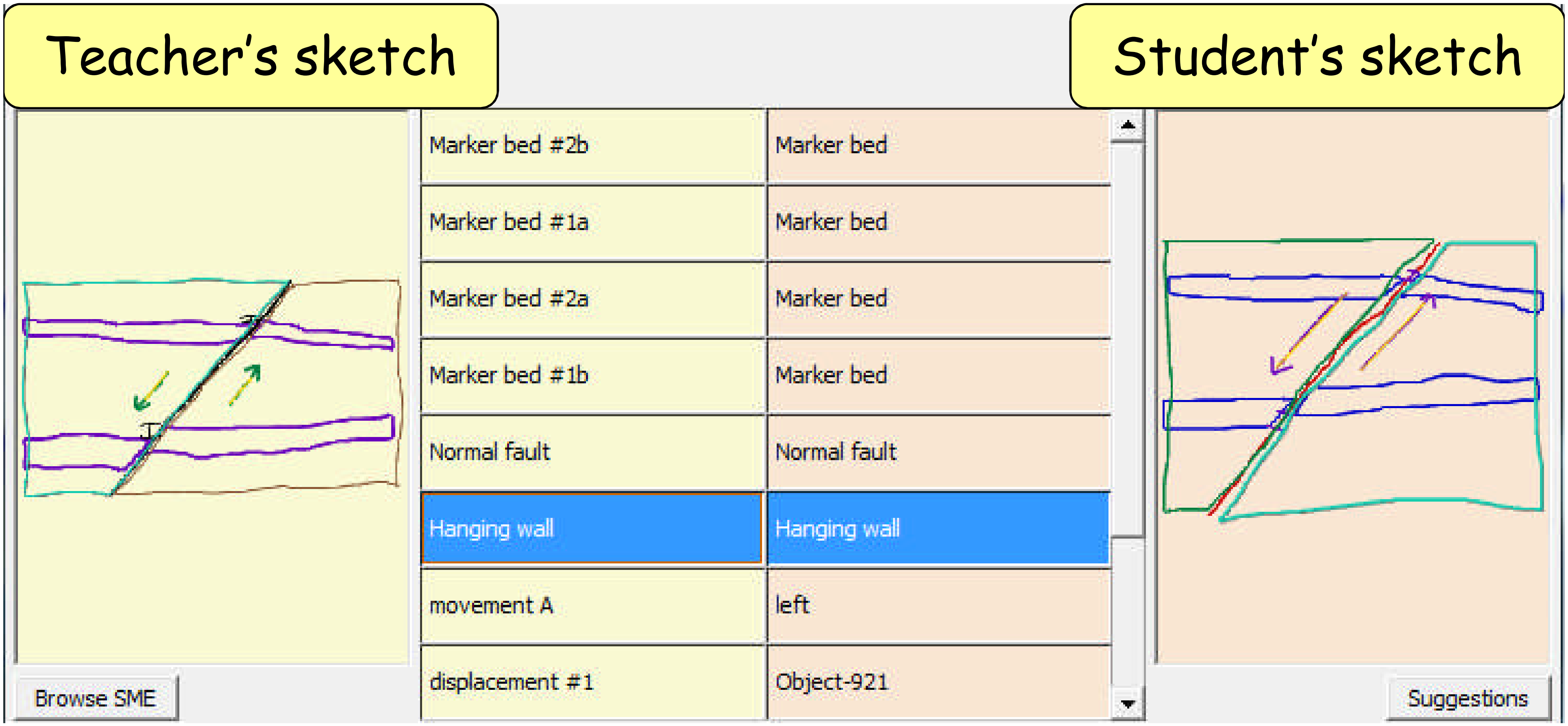
Worksheet Authoring Environment

- Create problem statement
- Draw solution sketch
  - CogSketch automatically generates facts
- Select subset of concepts student will see
- Add coaching advice for important facts



Coaching via Analogy

- Sketches are compared via the Structure-Mapping Engine (SME) to generate coaching advice
  - Candidate inferences of the mapping provide differences

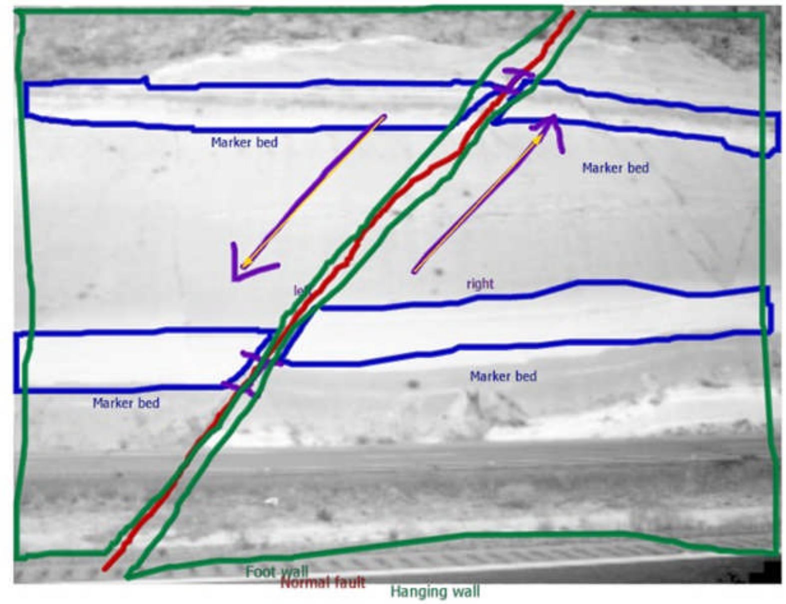


Grading Environment built into CogSketch

- CogSketch generates detailed analyses of student performance for grading
- Rubrics specified in authoring environment

Grading Report

student: TOSHIBA
worksheet: **Faults_1**
(c:\qrg\cogsketch\v0r01\experiments\geoscience-fall-2009\structural-geology\student-sketches\Faults_1.sk)



Total Score

normalized: **73.68** / 100 points

raw: **14** / 19 points

Scoring Details

Missing Glyphs

For each of the glyphs listed below, points are awarded if

Non-Quantitative Facts Important for Tutoring

The following are the facts marked as important for tutoring that don't mention

Student Score: 4 / 8 points

- [0 points]

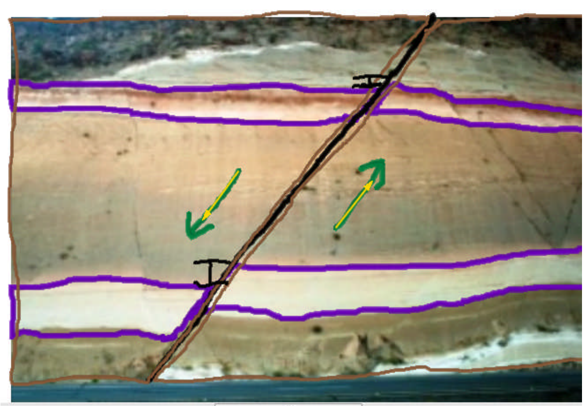
Correct Answer would be:
`(rightOf "Normal fault" "Hanging wall")`

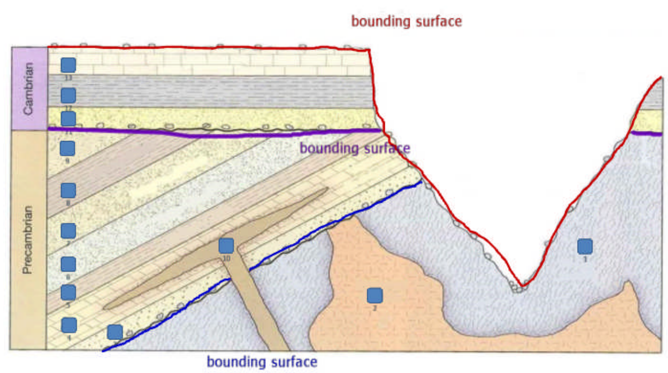
Student had the following similar facts:
`(rightOf "Foot wall" "Marker bed")`

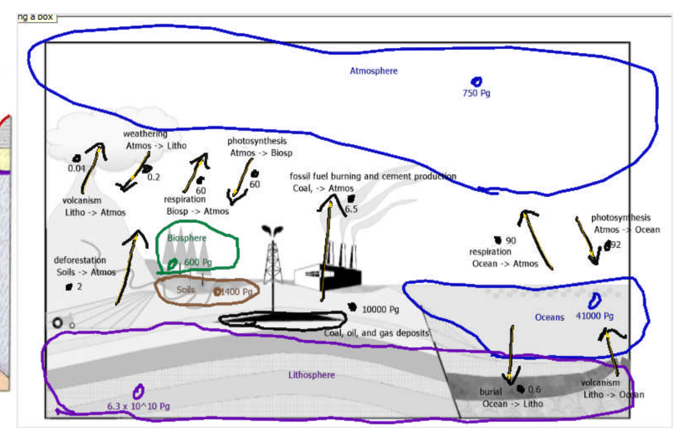
Worksheet Classroom Pilot Study

- Brad Sageman's Geo 201: Surface Processes, Fall 2009
  - 3 fault worksheets + ordering
  - Carbon Cycle
- Students used sketch worksheets successfully
- Students improved on using sketch worksheets through practice
- Carbon cycle worksheet indicated that the annotation instructions needed to be improved

Yin et al IAAI 2010







Worksheet Plans

- Expand participating geoscience classes at NU
- New connected set of worksheets being designed
  - Collaboration with Basil Tikoff, U. Wisconsin
  - Goal: Teach college geoscience students about how arrows are used, building on Jennifer Cromley's work
- Explore worksheets for middle school & high school assessment
  - Collaboration with Louis Gomez, U. Pittsburgh
- Opportunity: Incorporate knowledge tracing into CogSketch, using a pool of worksheets
  - Use results from laboratory and classroom studies to drive more advanced sketch-based tutoring

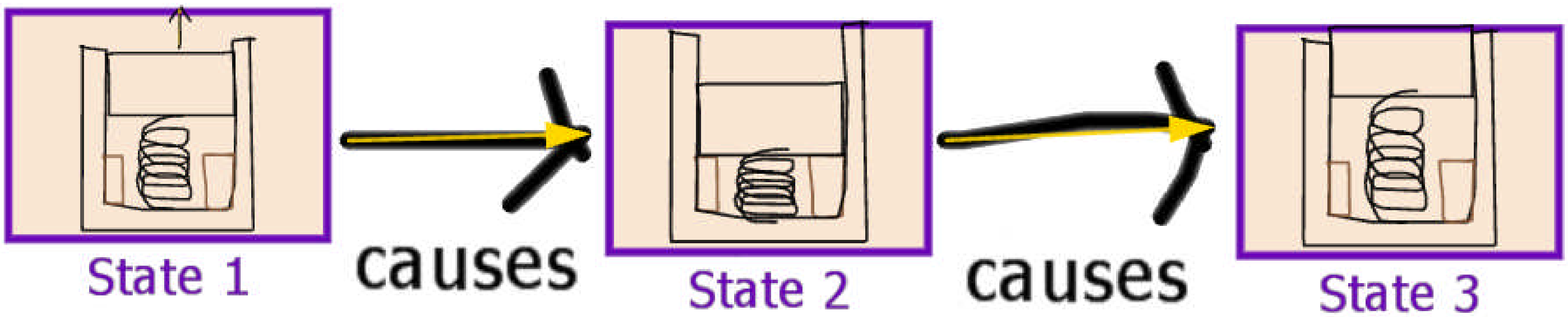
SILC

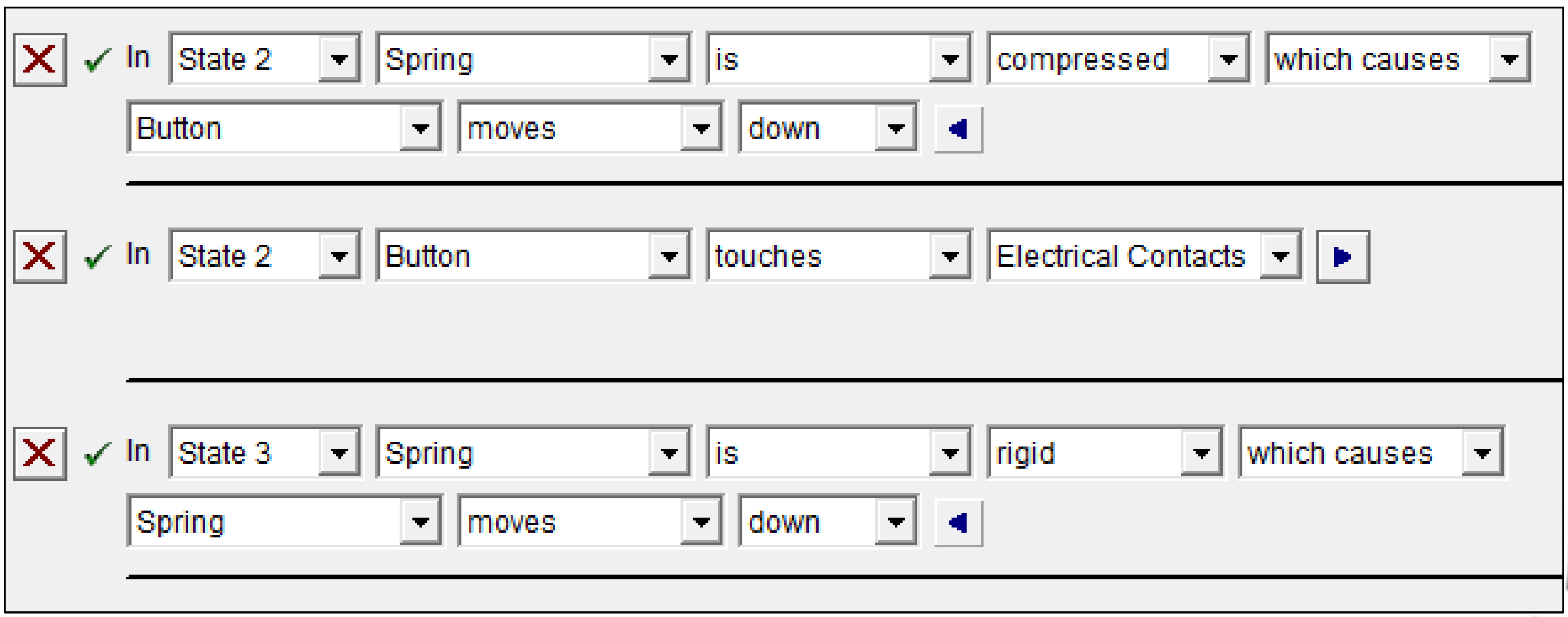
Design Buddy: Setting and Problem

Engineering Design and Communication Course
at Northwestern University

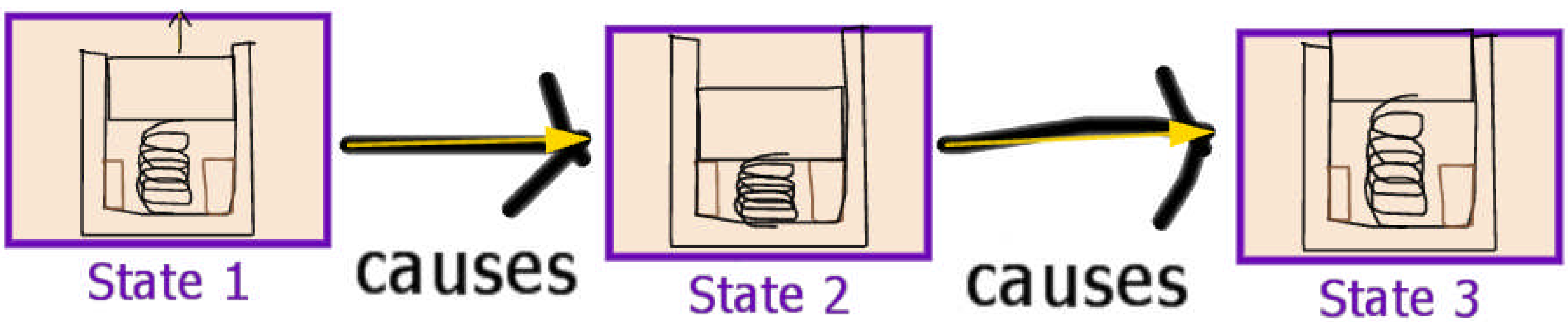
Problem:
Students have trouble using sketches to communicate

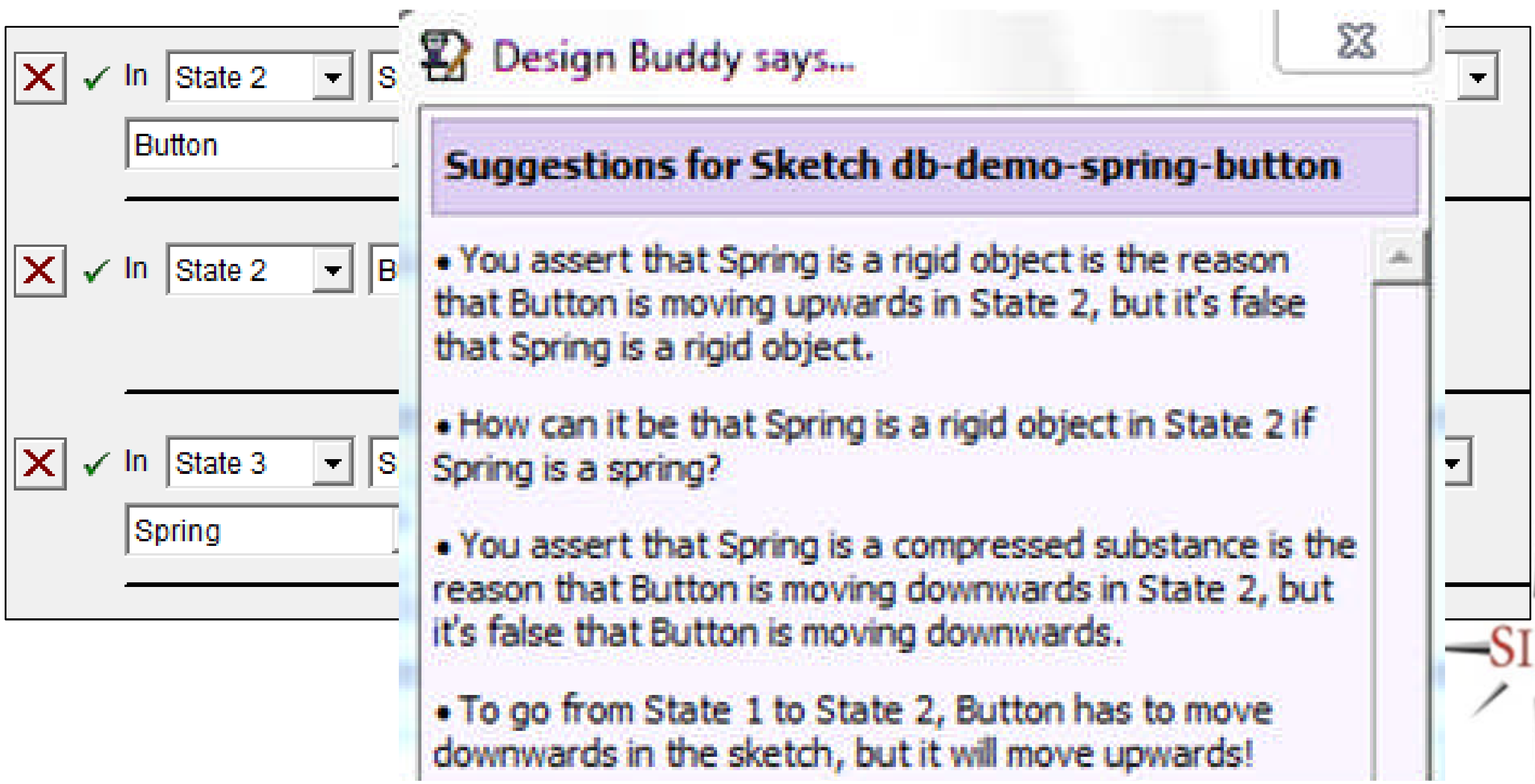
Design Buddy Finds Problems in Explanations





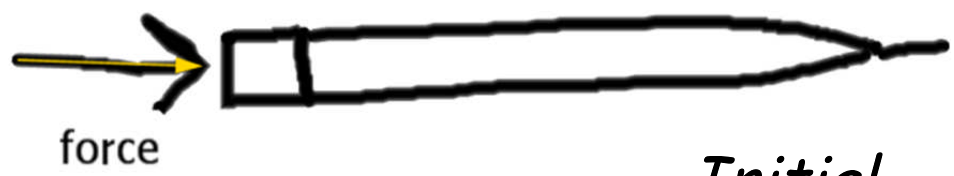
Design Buddy Finds Problems in Explanations



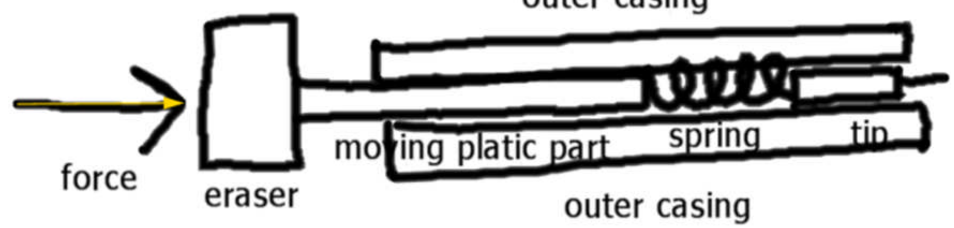


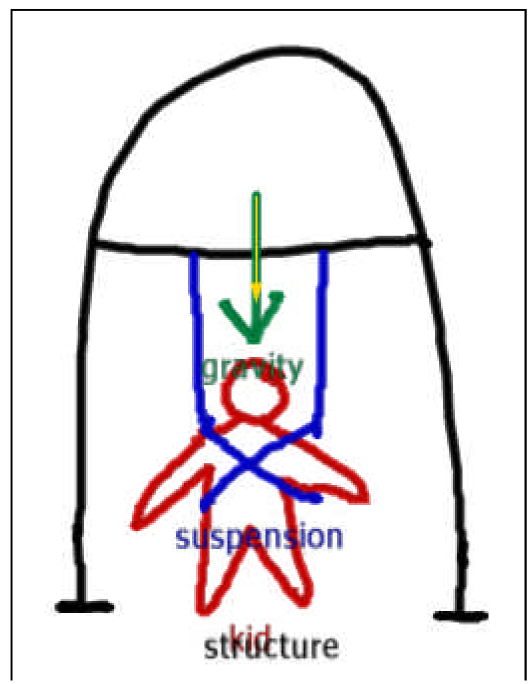
Pull-out studies with EDC students

- 15 minute tutorial
- Using Design Buddy to
  - Explain how a fountain pen works
  - Explain how their current design project worked
- Students were able to use Design Buddy
  - It mostly understood their explanations
  - Students improved their explanations through multiple feedback cycles
    - Mean: 5.5, min 3, max 8



Initial





Final

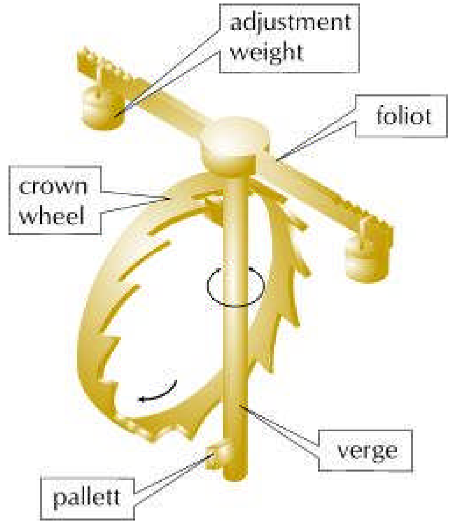
Wetzel & Forbus, QR 2010

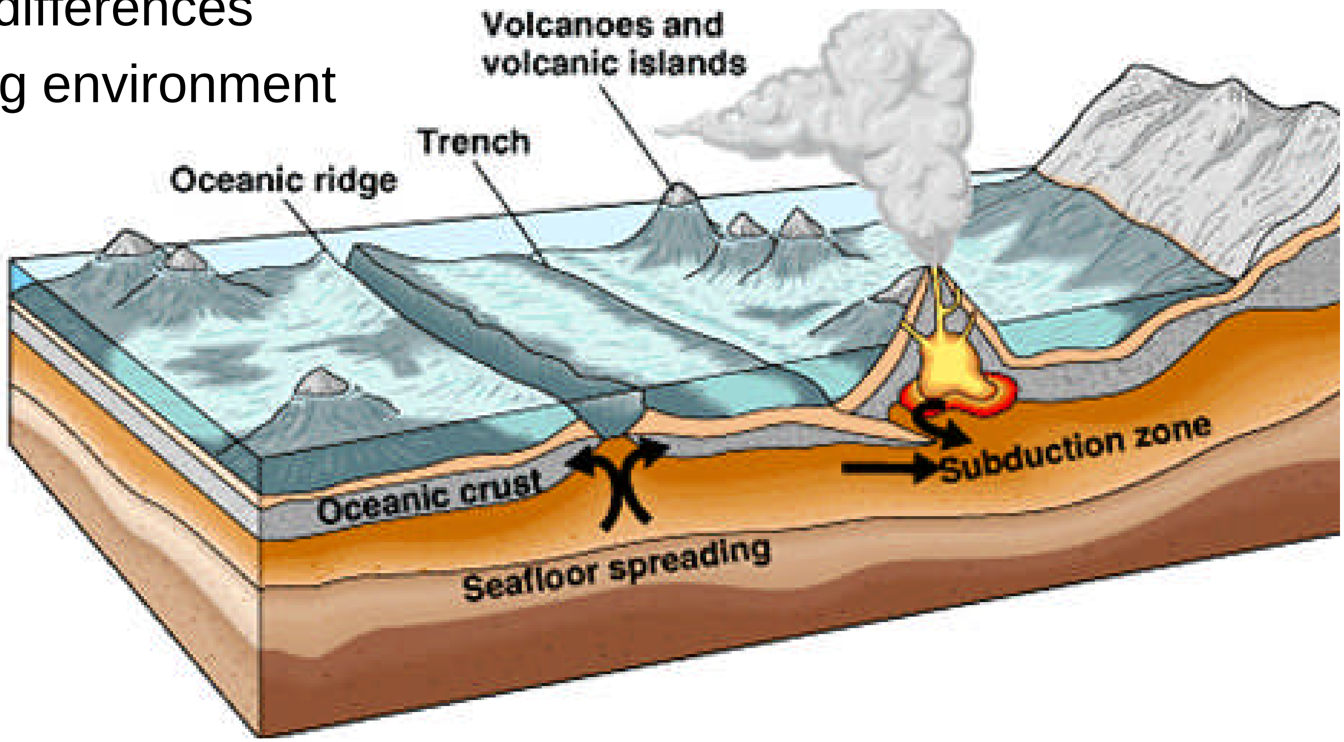
Next Design Buddy Experiment

- First in-class experiment
  - Explain their class design project
    - Instructors will grade sketched explanation
  - Evaluate the explanation created by another student
- Data to be collected
  - CogSketch: Timing data, explanation problems detected, student repairs.
  - Instructor feedback on quality of explanation
    - Goal: quantitative explanation quality metrics
  - Student feedback on Design Buddy
- Pilot in Fall, run in multiple sections in Winter, Spring

Basic research motivated by translation

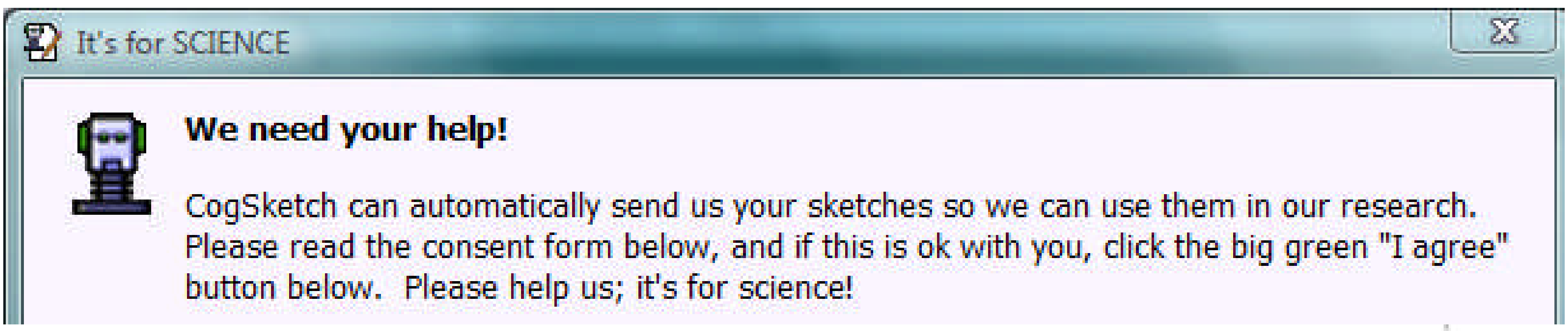
- Extend CogSketch with robust 3D reasoning & perception
  - Forces and surfaces
  - Non-rigid materials
- Expand visual/spatial routines processor
  - Model individual differences
  - Develop authoring environment





CogSketch: We want users!

- Psychologists: Time-stamped ink data often easier to analyze than video
- AI scientists: Message-passing API, to use as component with other software
  - Open-source in a year, in addition to regular binary releases
- Technical support provided for next 1-6 years



CogSketch Team + Collaborators

- CogSketch Developers
  - Ken Forbus
  - Jeff Usher
  - Andrew Lovett
  - Jon Wetzel
  - Maria Chang
- Weekly Contributors
  - Micah Goldwater (postdoc)
- Geoscience Collaborators
  - Brad Sageman (NU)
  - Basil Tikoff (Wisconsin)
- EDC Collaborators (NU)
  - Bruce Ankenman
  - John Anderson
  - Stacy Benjamin
- Psychology & Education Research Collaborators
  - Steve Franconeri (NU)
  - Dedre Gentner (NU)
  - Louis Gomez (Pitt)
  - Susan Levine (U Chicago)
  - Nora Newcombe (Temple U)
  - Terry Regier (U Chicago)
  - Tim Shipley (Temple U
  - David Uttal (NU)

http://www.spatiallearning.org

Translation in the Science of Learning Centers

Brief Introductory Comments

Broad meanings of "translation" and "translation research" reflected in the presentations

Learning research and education research: overlap and differences reflected in the presentations

A useful framework based on focusing on improvements in education as a complex system
(Maroulis et al. Science Oct. 1st, 2010)

"mechanism based" *(micro-level)*
"effects based" *(macro-level)*

Translational Work at CELEST and LIFE

CELEST

* Heather Ames Versace: The applied neuroscience of learning
* Jonathan Brumberg: Brain-computer interfaces for communication
* Massimiliano Versace: Brain-inspired computing

LIFE

* Roy Pea: Augmenting educational designs with social learning
* Bill Penuel: Curriculum design studies focused on leveraging personal relevance and social practices in elementary science
* Dan Schwartz: Different models of the relation between research and translation

Translational Work at PSLC and SILC

PSLC:

* Ken Koedinger: In vivo experiments and cumulative theory as keys to translation
* Vincent Aleven: From research to practice – Interactive examples and diagrammatic self-explanation in an intelligent tutoring system
* David Klahr: Classroom experiments with TED, the Tutor for Experimental Design

SILC:

* Nora Newcombe: SILC's strategy for supporting STEM education through spatial learning
* Dedre Gentner: Supporting early STEM learning with spatial analogy and language
* Ken Forbus: Translating sketch understanding from laboratories to classrooms, and back again

Translational Work at TDLC and VL2

TDLC:

* Gary Cottrell (UCSD): Overview of at TDLC
* Terri Jernigan (UCSD): A neurodevelopmental case for personalizing education
* Sean Kang (UCSD) : Distributed practice over the long-term: Should spacing be expanding or equal interval?

VL2:

* Thomas Allen (Gallaudet) : Overview of translation at VL2
* Donna Morere (Gallaudet) : Identifying factors influencing early literacy for deaf students through longitudinal study of student, family, and school characteristics

Closing Comments

Where is the research focused?

What lies behind considerations of "Fidelity" and "Adaptation"

Fidelity to the *design*
Adaptation to the *environment*

A key challenge facing education research is to integrate insights about "micro-level" mechanisms with evidence about aggregate, "macro-level" outcomes that emerge from processes of implementing those mechanisms.

On a personal note, from translation research to implementation research

Looking at education as an integrated *complex system* whose outcome is learning:

Where is the missing research?

"Adaptation" to an environment (i.e. learning within organizations)

¨Sustainability" of improved environments (i.e. learning by the educational organization)

TDLC Translational Research

Overview

Our overall goal:
Translating Basic Science into “Best Practices” in Education

Synapses
↓
Circuits/ Systems
↓
Computational Strategies
↓
Behavior
↓
Learning In The Classroom

- *A set of teaching tools that promote rapid learning, superior retention, and flexibility of information use, based on learning principles of the brain.*

- *Improved intervention for children struggling with English language and reading skills.*

- *Improving face recognition, emotion recognition, and cultural differences within these domains to impact teacher/student interactions.*

- *Perceptive robot systems for teaching and intervention.*

QuickTime™ and a decompressor are needed to see this picture.

Multiple approaches to translation

- **Traditional**: Lab -> Classroom (FFW+PTR)
- **Traditional++**: Use modeling -> optimize spacing
- **Inreach**: Classroom -> Lab (gamelan)
- **Interactive**: (RUBI, LFI!)
  - Lab->Classroom->Lab->Classroom->Lab…
- **Serendipity:** Encourage basic research that we *hope* will lead to translation

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- **Serendipity:** Encourage basic research that we *hope* will lead to translation

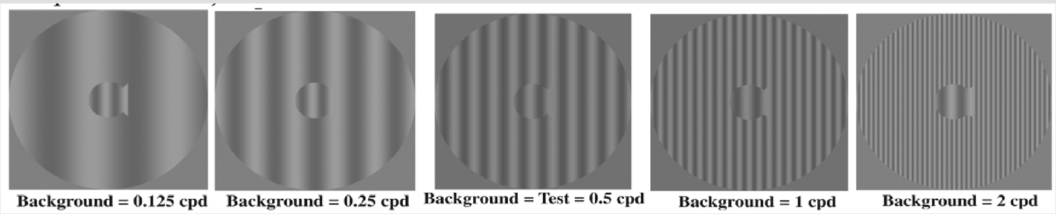
“Traditional” translation (Lab-> Classroom):

Leveraging our partnership with Scientific Learning Corp.

- *Fast ForWord* tries to remediate dyslexia by speeding the temporal processing of the auditory system.
- Faster temporal processing ->
- Better phonological representations ->
- Better targets for phonics ->
- Better reading

"Traditional" translation (Lab-> Classroom):
Leveraging our partnership with SLC

- *Path To Reading* tries to remediate dyslexia by speeding the temporal processing of the visual system (magnocellular, or motion pathway).



- Faster temporal processing ->
- Better onset/offset signals to the shape (parvocellular) system during eye movements -> Better reading

“Traditional” translation (Lab-> Classroom):

- Interactions between Visual and Auditory Interventions in Reading (collaboration between Cottrell (UCSD), Lawton (Perception Dynamics Institute) and Jenkins (Scientific Learning) (Funded in 2010 by IES $2.3M)
- Scientific question: will speeding up timing in the visual system and the auditory system have a synergistic effect, giving superadditive results?

	No *FFW*	***FFW* (auditory training)**
No *PTR*	<u>Control Groups:</u> (1) Business As Usual; (2) Hawthorne effect control: Orientation Discrimination Training	*FFW* only group
***PTR* (visual training)**	*PTR* only group	Combined *FFW* & *PTR* group

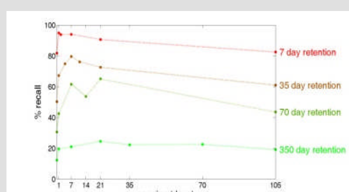
Multiple approaches to translation

- **Traditional**: Lab -> Classroom (FFW+PTR)
- ***Traditional++: Use modeling -> optimize spacing***
- **Inreach**: Classroom -> Lab (gamelan)
- **Interactive**: (RUBI, LFI!)
  - Lab->Classroom->Lab->Classroom->Lab…
- **Serendipity:** Encourage basic research that we *hope* will lead to translation

Translation++:
Using modeling to optimize learning

- Mike Mozer is a modeling God.

Mike

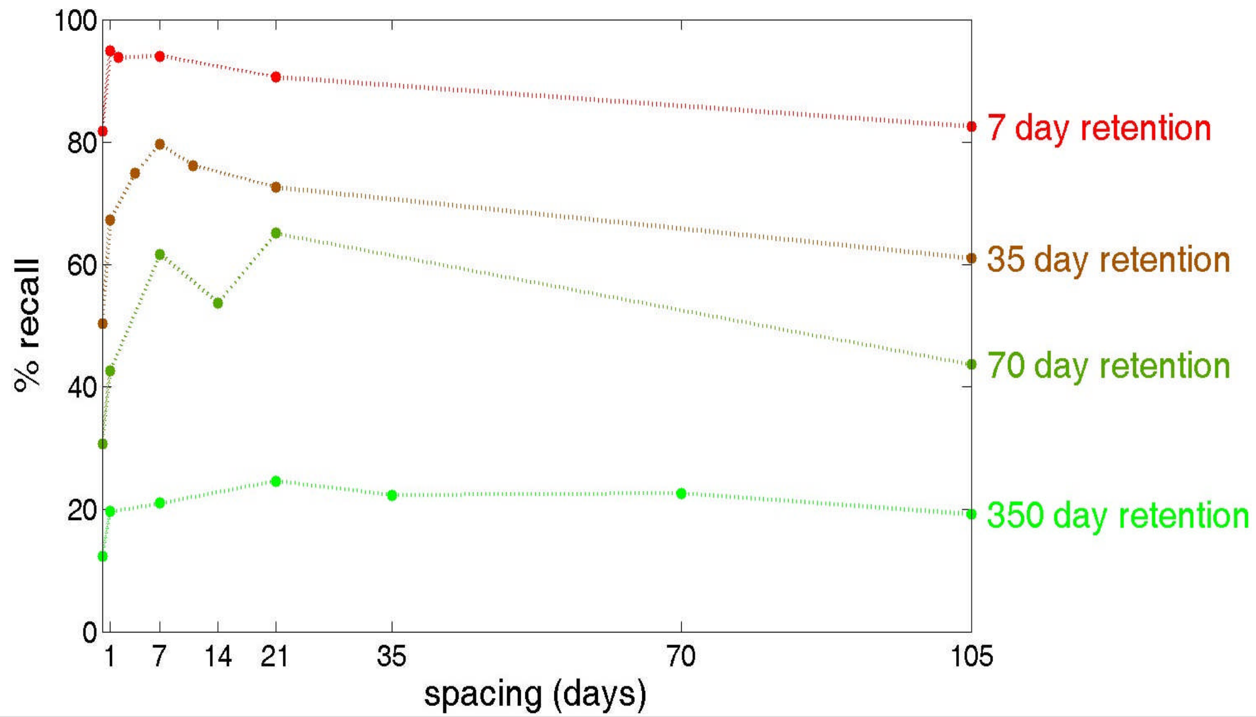


Cognitive phenomena
to be modeled

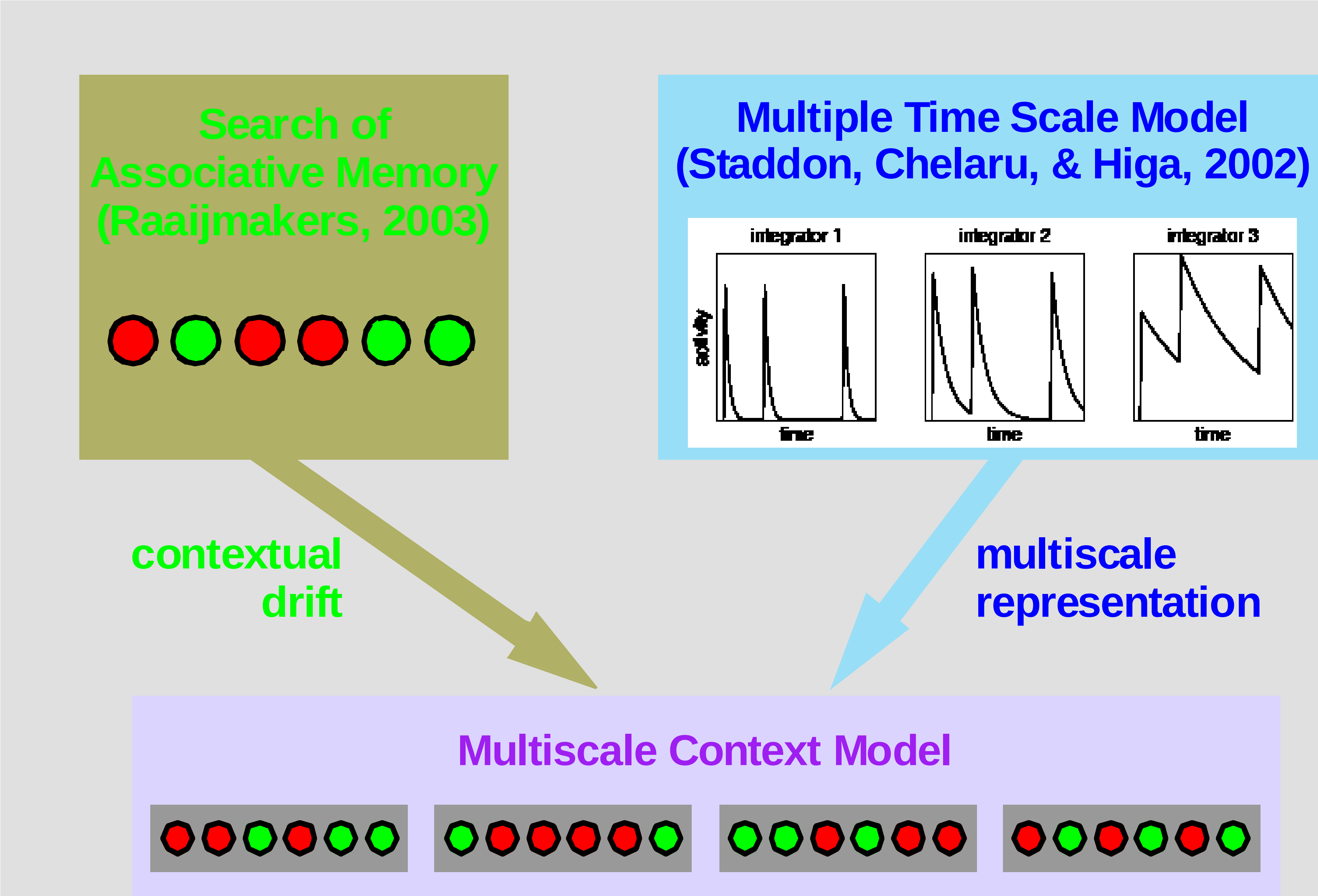
QuickTime™ and a decompressor are needed to see this picture.

The data: Forgetting curves by retention interval versus spacing of study episodes

Cepeda, Vul, Rohrer, Wixted, & Pashler (2008)
(collected via a web-based experiment)

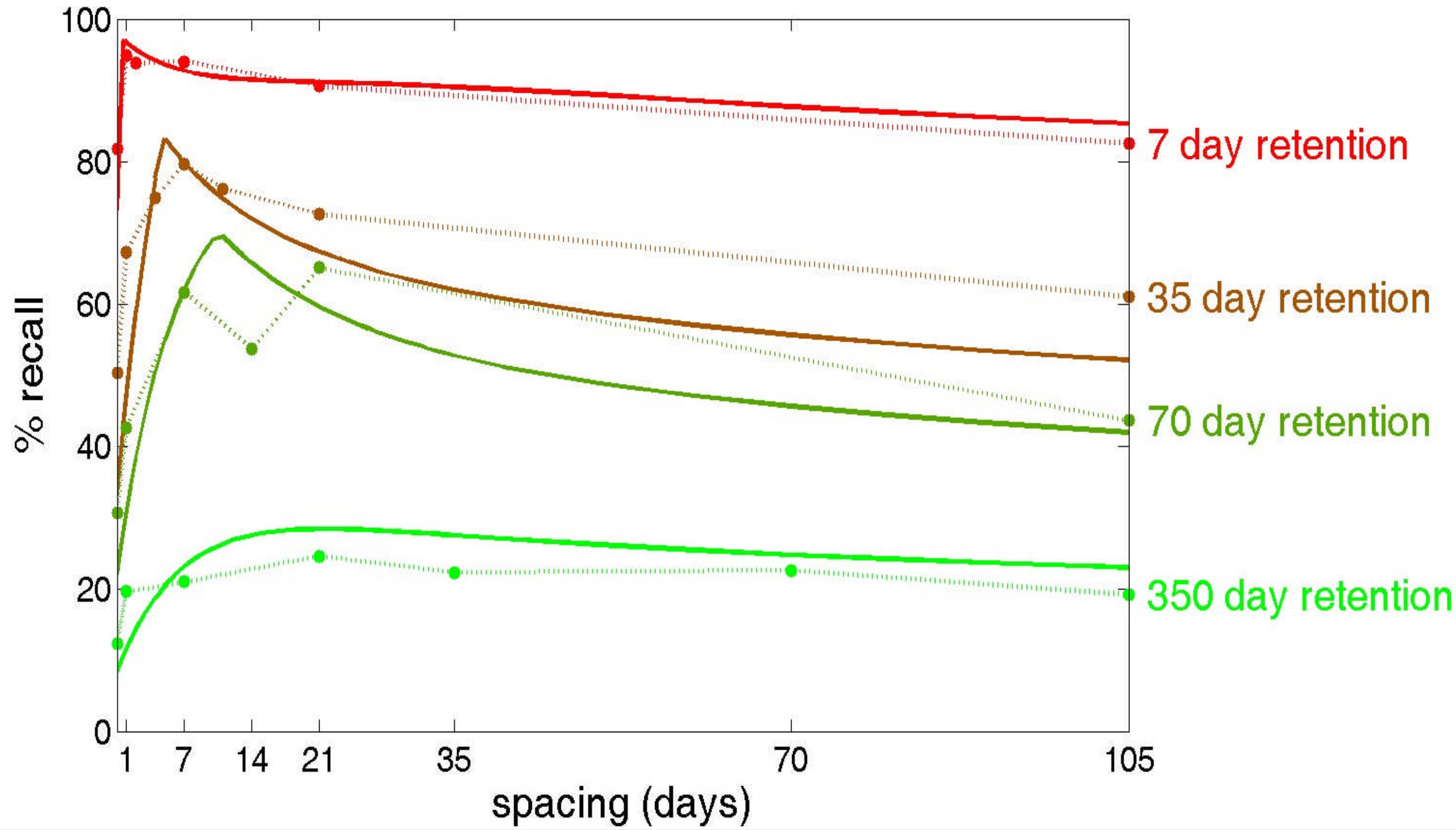


Note the optimal spacing depends on when you want to remember the items…


Search of
Associative Memory
(Raaijmakers, 2003)
Multiple Time Scale Model
(Staddon, Chelaru, & Higa, 2002)
integrator 1
integrator 2
integrator 3
activity
time
time
time
contextual
drift
multiscale
representation
Multiscale Context Model

Mozer's model *predicts* the data (solid lines)

based on fits to a forgetting curve from *separate data*



Using the model to *optimize retention*

- Working backwards from the model, Pashler & Mozer have now developed a web-based training system for Boulder students learning second language vocabulary.
- The model schedules items for learning episodes to optimize retention on the Final Exam
- Now making it an iPhone app…

Psychology meets Computational Modeling meets Education!

Multiple approaches to translation

- **Traditional**: Lab -> Classroom (FFW+PTR)
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- **Serendipity:** Encourage basic research that we *hope* will lead to translation

The Gamelan Project: *Synchronicity*: Social learning, temporal perception, and music

(Chiba (UCSD), Reilly (SDSU), Makeig (UCSD), Minces (UCSD) Tallal (Rutgers) **Alex Khalil** (Museum School))

- Balinese Gamelan, of all the world's musical styles, values ***ensemble synchrony*** most highly.
- In teaching this music to elementary school children, Ethnomusicologist Dr. Alex Kahlil observed that an inability to synchronize in an ensemble seems to correlate with the presence of ADHD.
- He came to Andrea to see if this could be tested: *Inreach!*

The Gamelan Project

- Goal: Use high tech *gamels* (hammers) and computational analysis to assess the hypothesis.
- Use EEG markers of attention to correlate with performance on this task.
- Investigate whether musical training can ameliorate attentional and academic performance - and normalize the EEG markers.

QuickTime™ and a
decompressor
are needed to see this picture.

Inreach: Classroom->Lab

High tech “gamelan” instruments using piezoelectric sensors…
Data analyzed using neural spike coherence techniques
Early results show a negative correlation with attentional measures

The Gamelan Project

- As part of this project, low SES, diverse children from the Hoover schools in San Diego will:
  - Receive free music training
  - Come to UCSD for assessments
  - Be exposed to TDLC research: MoCap/Brain Dynamics, Robots, CERT…
- The project will thus combine *diversity, outreach, education,* and *research* - and it was the result of *inreach*!

Multiple approaches to translation

- **Traditional**: Lab -> Classroom (spacing)
- **Traditional++**: Use modeling -> optimize spacing
- **Inreach**: Classroom -> Lab (gamelan)
- ***Interactive: (RUBI, LFI!)***
  - ***Lab->Classroom->Lab->Classroom->Lab…***
- **Serendipity:** Encourage basic research that we *hope* will lead to translation

Interactive Translation

- Try things out *before* the basic science is done!
- See what works and what doesn't
- Refine, retry (The Scandinavian Approach to Design)
- RUBI started out in Javier's garage, scaring his son.
- When his son liked how she looked, she was ready for the classroom.

Interactive Translation

- But the six-degree of freedom multi-joint arms that Javier's team was so proud of *scared the teachers*!
- So she became a BSA (Birmingham Small Arms) Robot…

QuickTime™ and a decompressor are needed to see this picture.

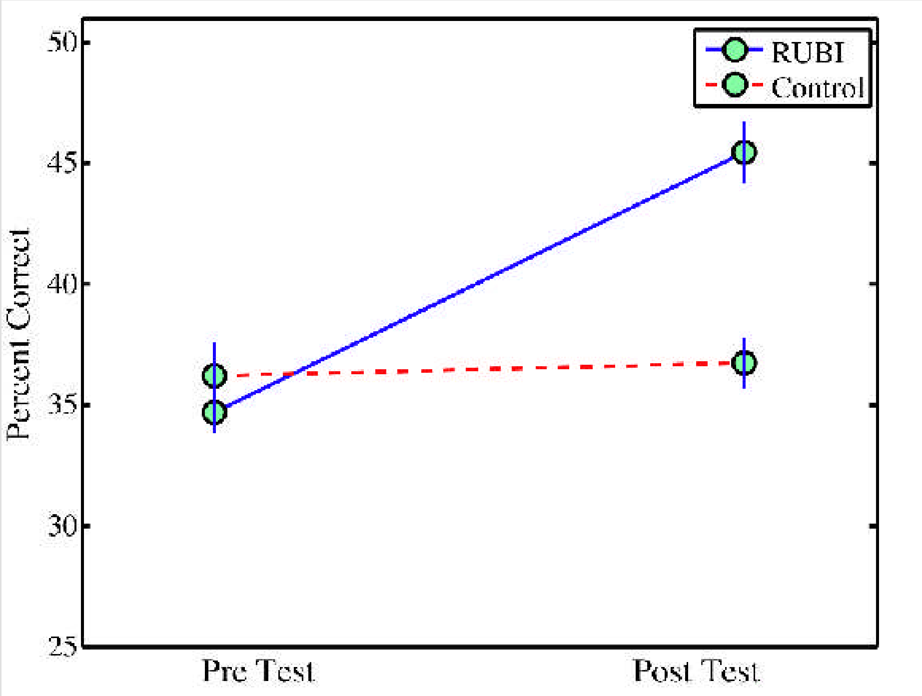
Interactive Translation

- But the kids would pull her arms off!
- So they had to make RUBI cry when her arms were pulled on…
- They started with Wizard of Oz simulations (man behind the curtain)

- Now RUBI is a completely autonomous low-cost social robot that can be deployed in an early childhood day care setting.

QuickTime™ and a decompressor are needed to see this picture.

Interactive Translation



• 10 day immersion with RUBI 10% improvement in word learning

Interactive Translation: RUBI crying for attention

QuickTime™ and a
decompressor
are needed to see this picture.

Interactive Translation: RUBI crying for attention

- It is this *social aspect* of RUBI that makes her a useful teaching tool - the children interact with her as if she were another child.
- As Pat discussed, she is an excellent vocabulary teacher, can teach colors and shapes according to the California standards for preschoolers…
- And the teachers *like* RUBI - even though she can’t join the union…

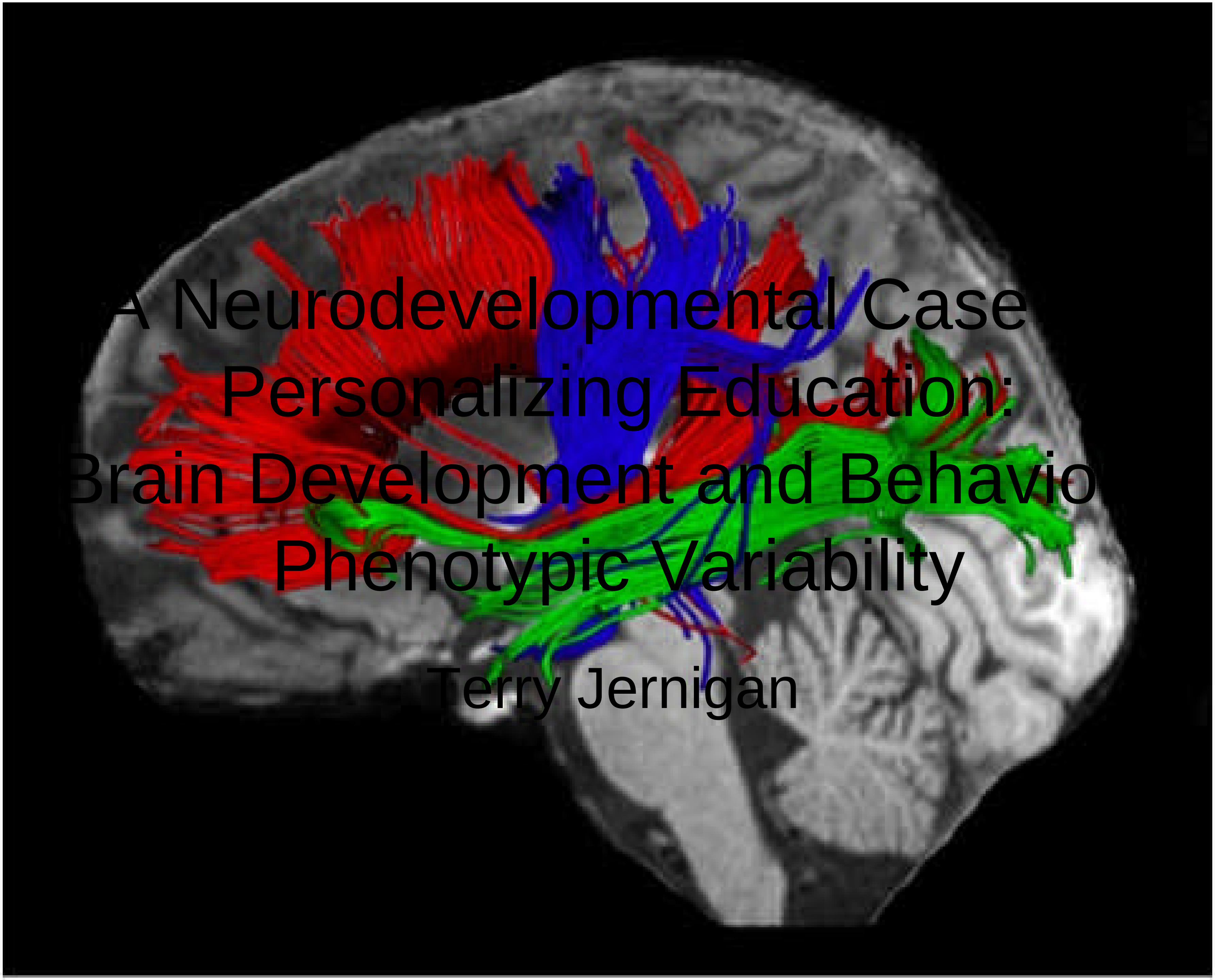
Multiple approaches to translation

- ***Serendipity: Encourage basic research that we hope will lead to translation***
- ***We'll just have to wait and see…***

QuickTime™ and a decompressor are needed to see this picture.

Summary

- I described a subset of our translation projects…
- We have a variety of approaches to translation - all based on sound science, all having timing as a central aspect.
- We will now hear about two more projects from Terry Jernigan (DTI in the schools!) and Sean Kang (more on spacing)
- Questions?



A Neurodevelopmental Case
Personalizing Education:
Brain Development and Behavio
Phenotypic Variability

Terry Jernigan

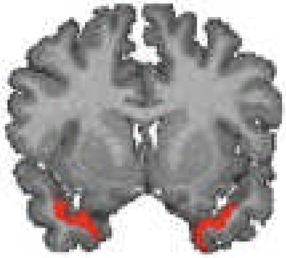
Preview

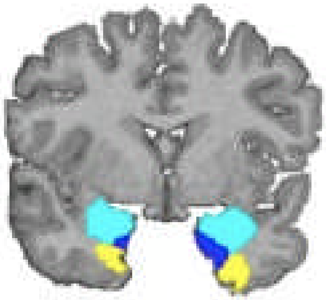
- Imaging reveals surprising alterations in neural tissues throughout childhood.
- Diffusion imaging adds new information about brain connectivity.
- Neural architectural variability is linked to behavioral phenotypes and to common genetic variation.
- What does it mean for educational technologies?

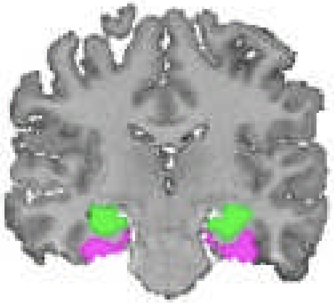
Conventional View of Brain Morphology in 1980's

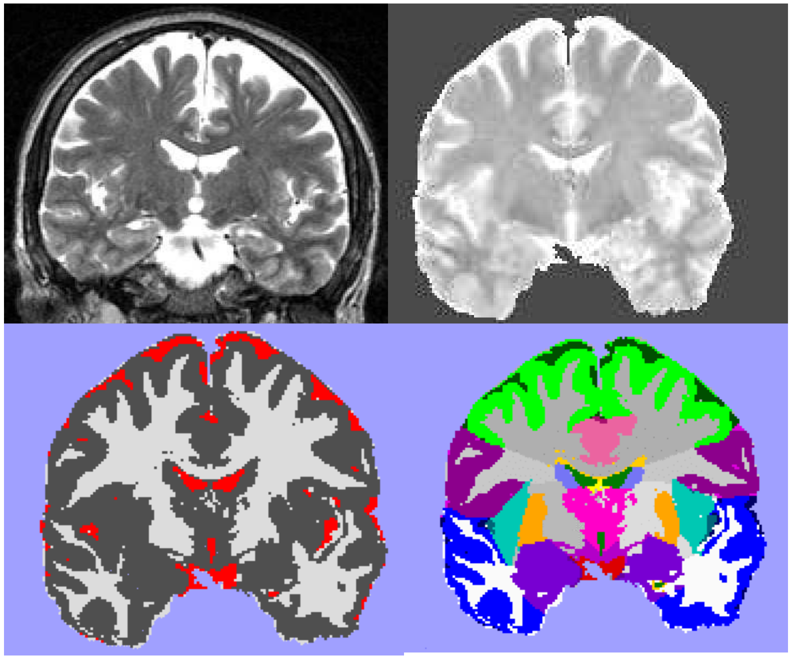
- Brain size and morphology are adult-like in school-aged children.
- Brain morphological characteristics are stable across childhood, adolescence, and adulthood.
- Atrophy of some brain structures begins in old age.

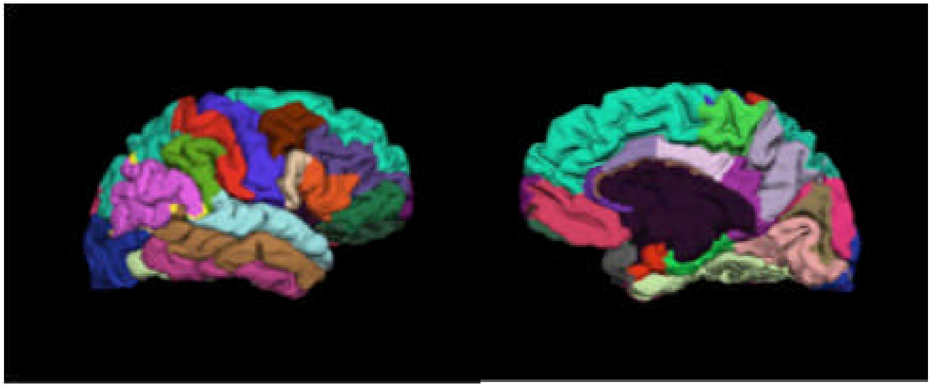
Brain Morphometry



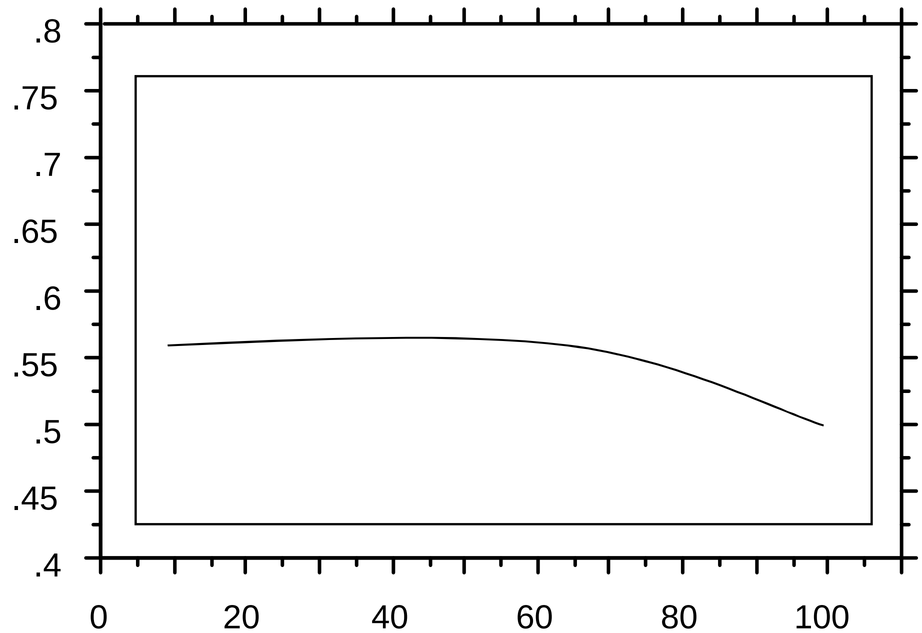








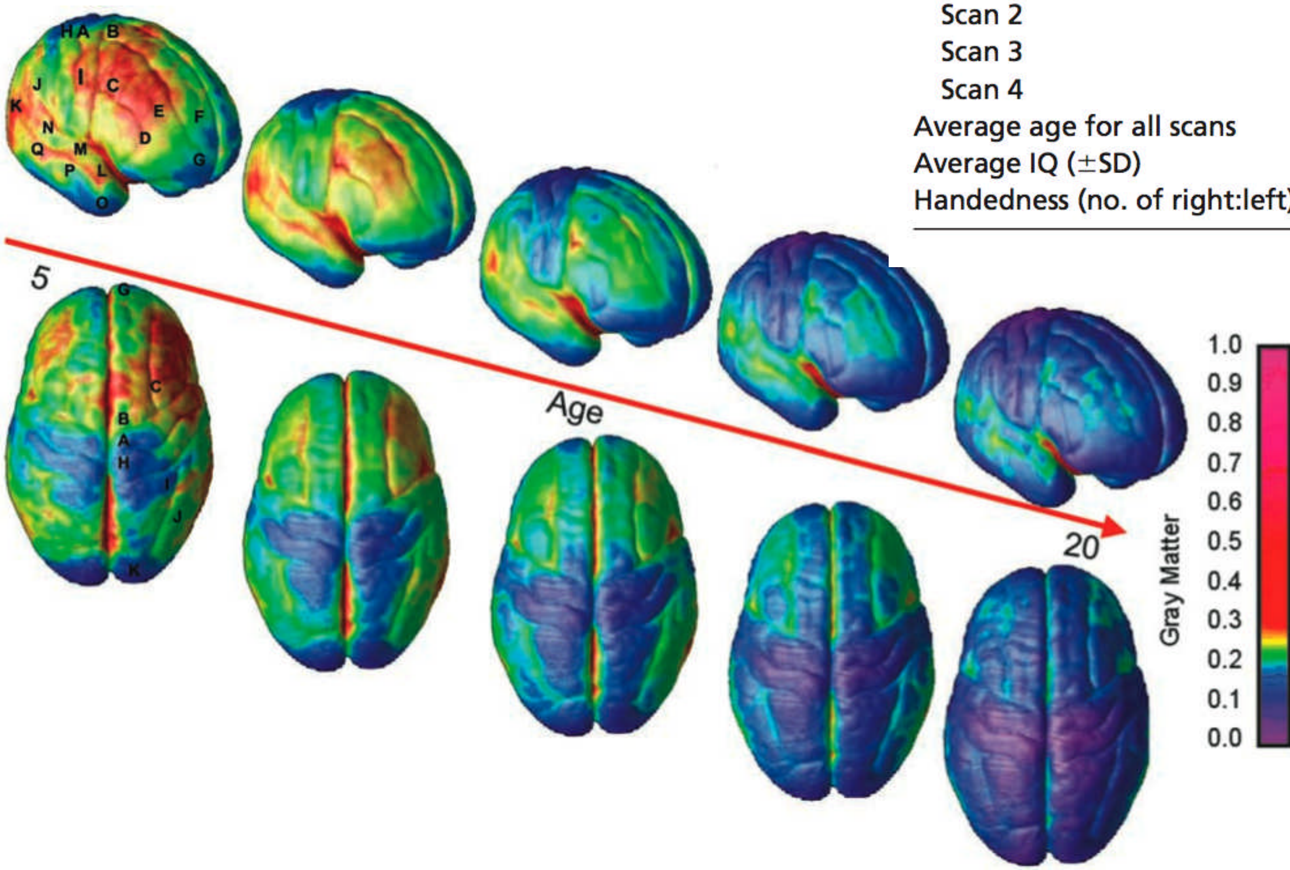
Age-Related Alterations of
Normalized Cerebral Gray Matter Volume

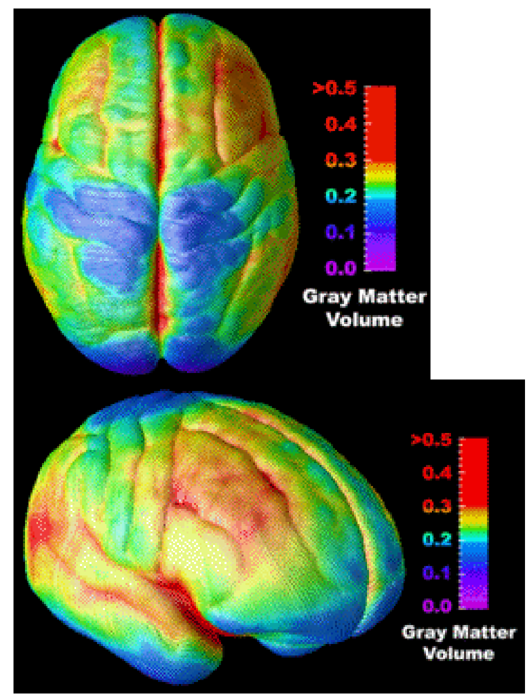


Mapping of Cortical Thinning with Longitudinal MRI Data
Gogtay et al., PNAS, 2004

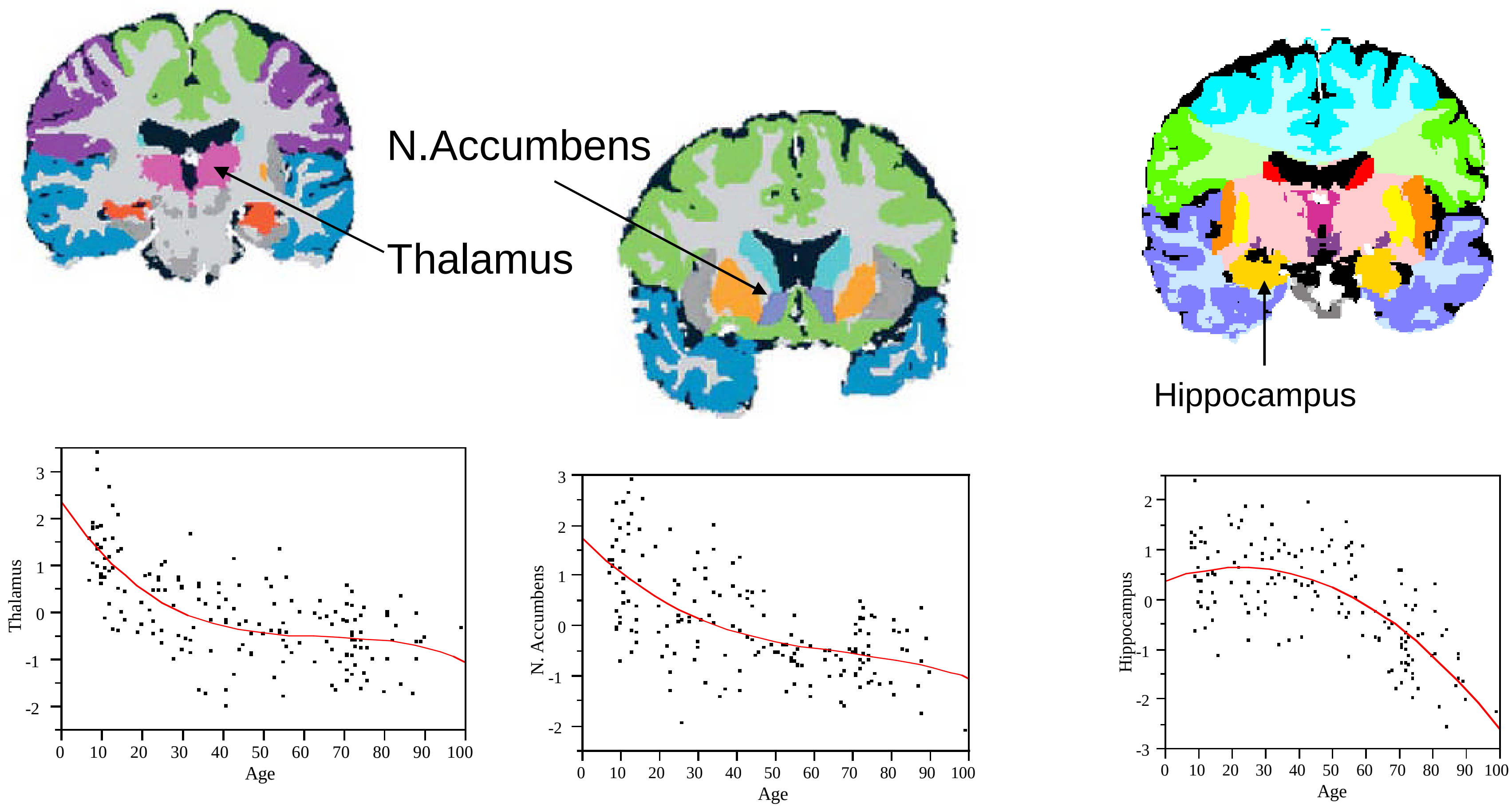
Table 1. Demographics of the study sample

No. of subjects	13
Gender (no. of male:female)	6:7
Total no. of scans	52
Average age (±SD) at	
Scan 1	9.8 ± 3.8 years
Scan 2	11.7 ± 4.1 years
Scan 3	13.8 ± 4.4 years
Scan 4	16.7 ± 4.3 years
Average age for all scans	13.0 ± 4.8 years
Average IQ (±SD)	125.8 ± 12.7
Handedness (no. of right:left)	12:1

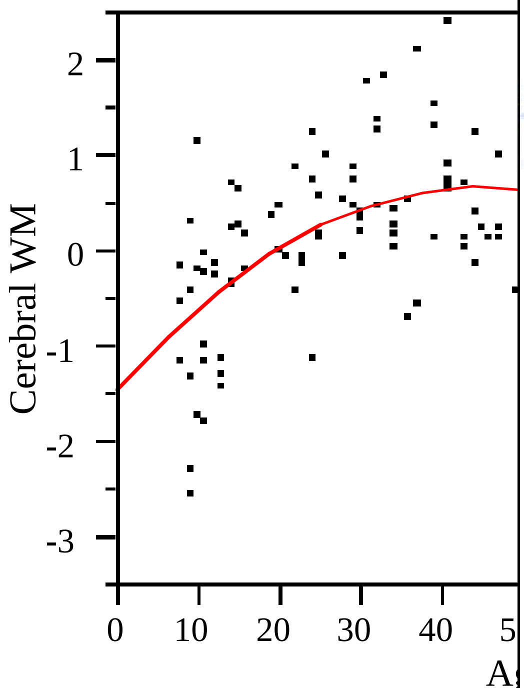


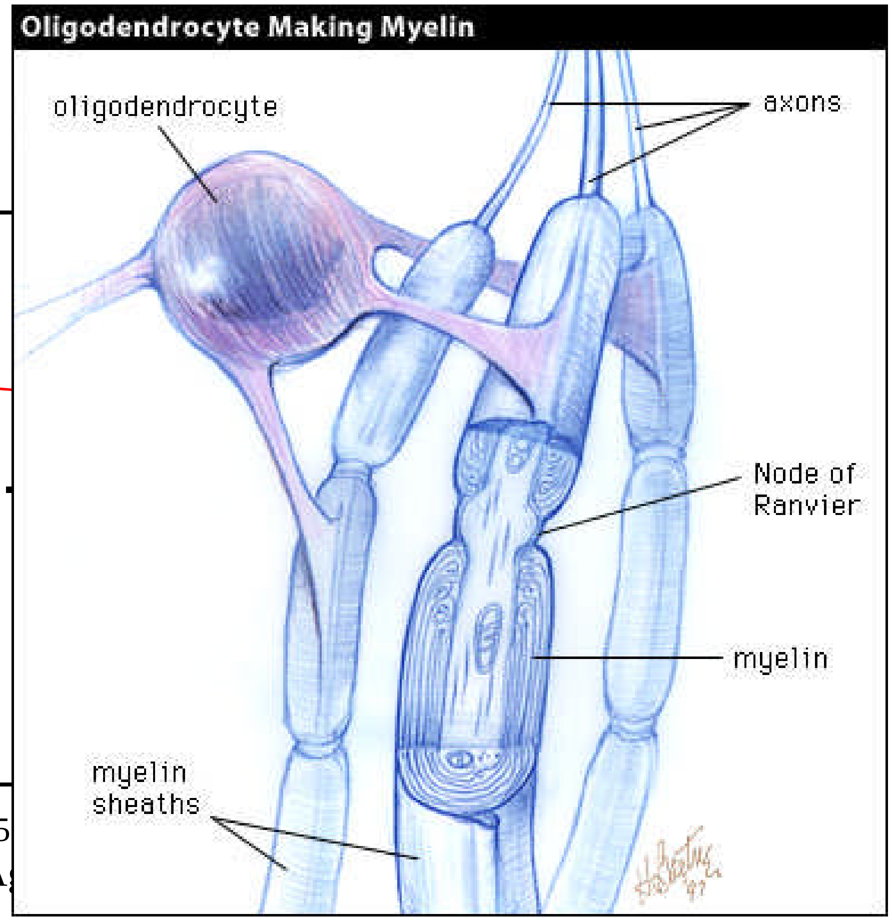


Age-Associated Alterations in Volumes of Subcortical Structures



White Matter Growth Associated with Post-natal Proliferation of Oligodendrocytes and Myelin Deposition



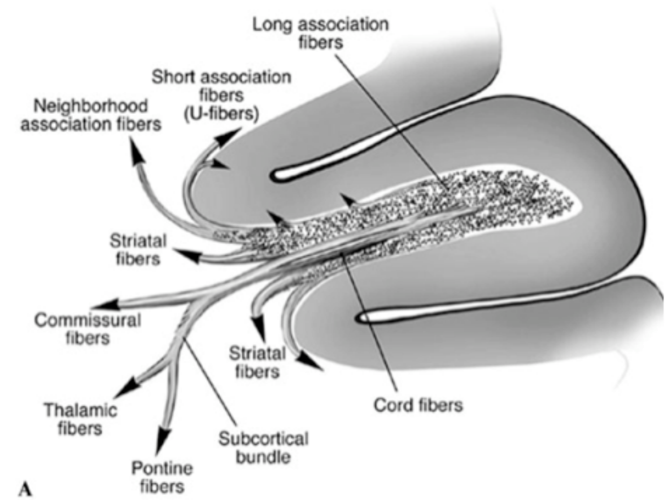


Early MR Morphmetry Results

- During the first 2-3 decades of life, age-related tissue alterations, presumably related to brain maturation, can be observed with morphometry.

- Though the first evidence came in the form of apparent changes in the morphology of gray matter structures, it was suspected that much of the change was directly, or indirectly, related to continuing myelination and fiber tract development.

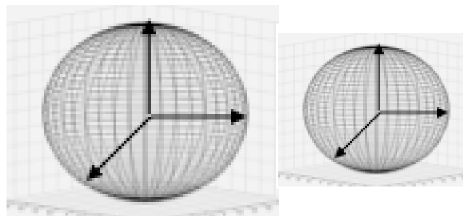
- However, until recently, further inves maturation was limited by the lack o structure with existing MR methods.



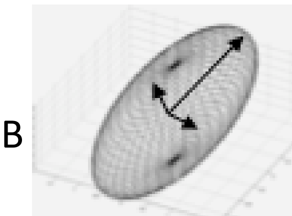
Diffusion imaging provides new information about brain connectivity

Diffusion Tensor Imaging

A

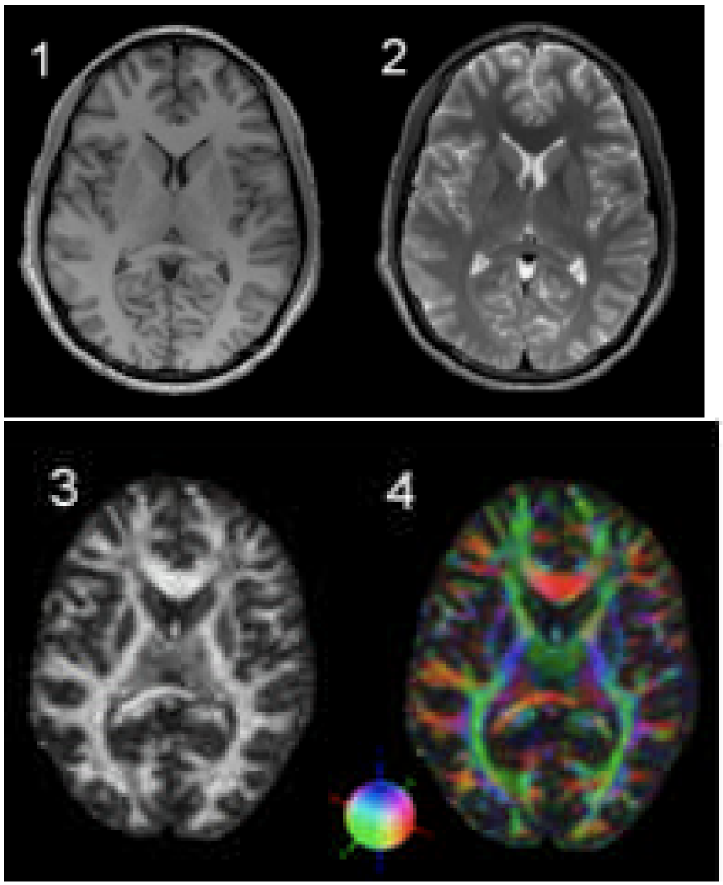


B



- Measures diffusion (motion) of protons in water molecules.
- Magnitude and direction of proton motion within a voxel can be described by a “tensor”.
- Proton diffusion in CSF and gray matter is relatively isotropic .
- The linear structure of fiber tracts constrains proton diffusion and produces **anisotropy**.

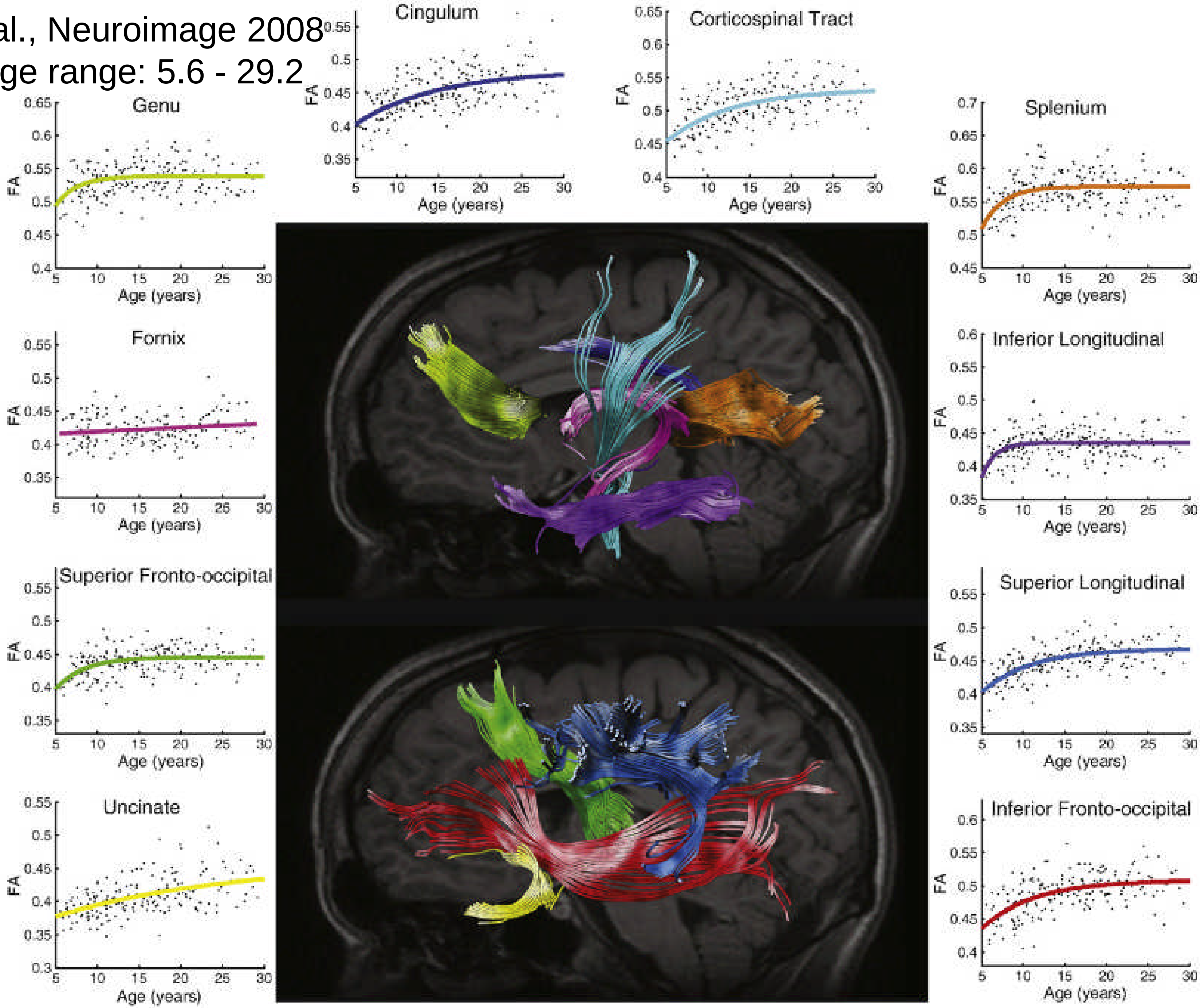
Diffusion Imaging Reveals Locations of Brain Fiber Tracts

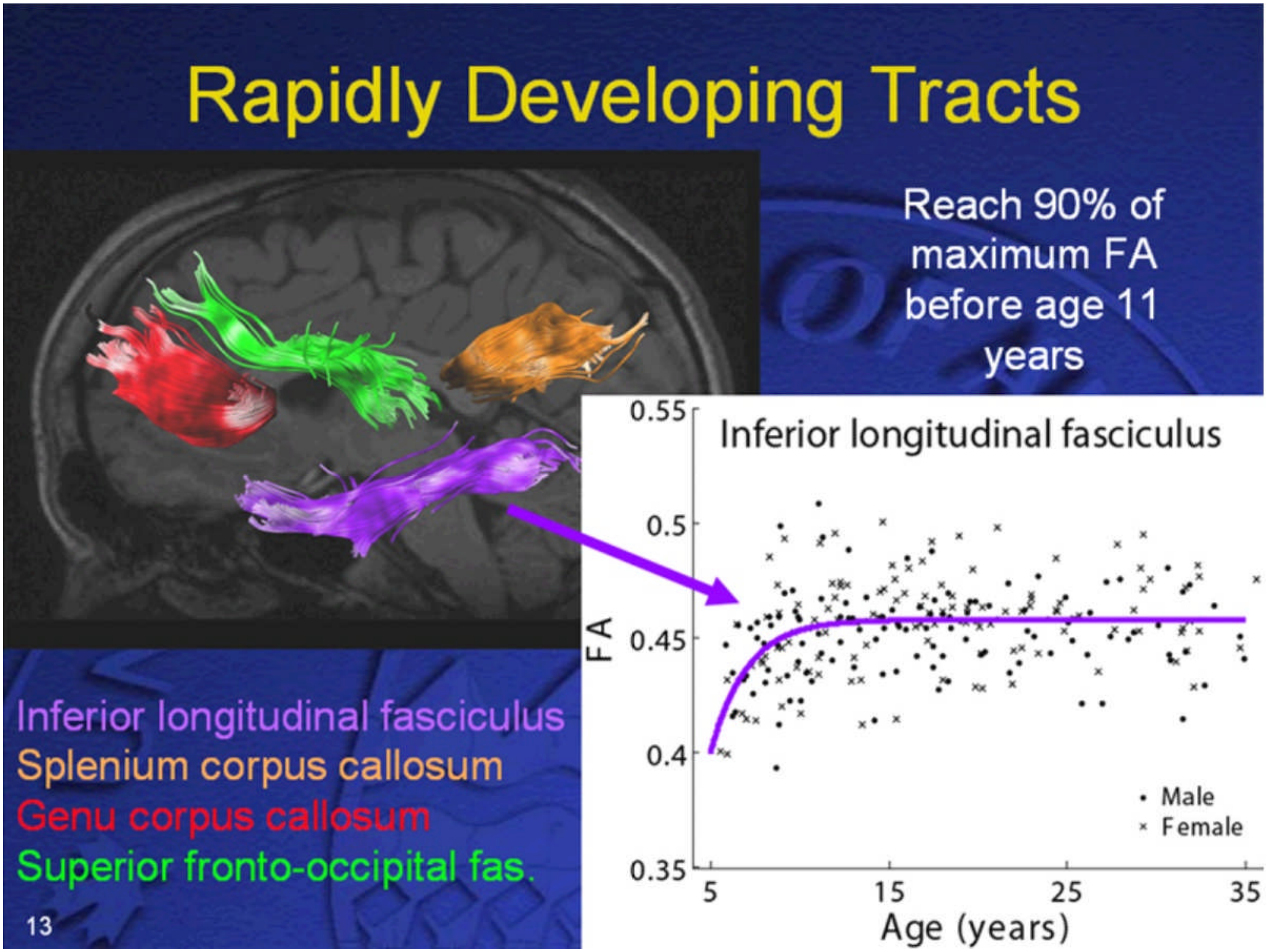


Diffusion Imaging of Brain Development

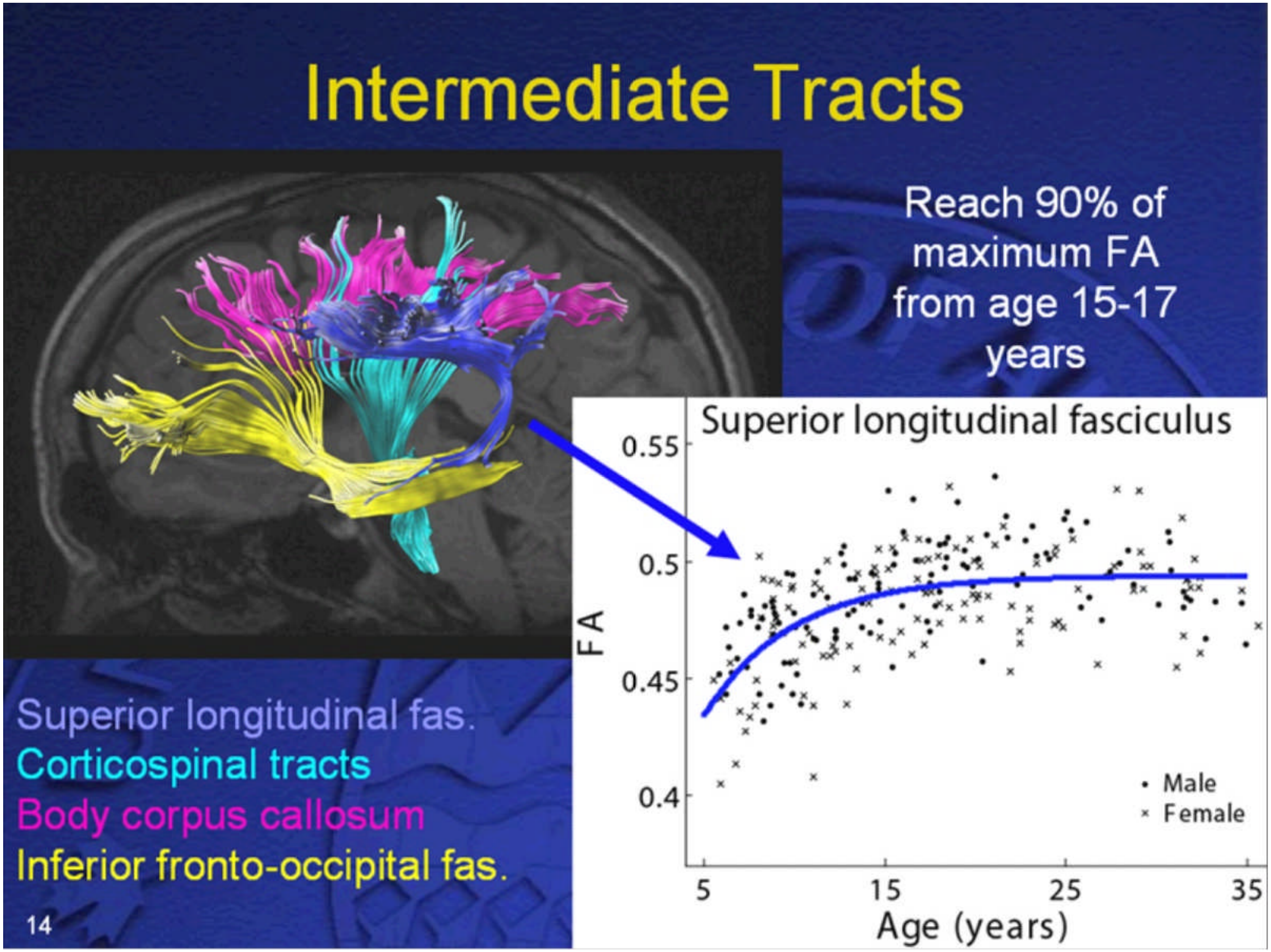
- During development, increasing myelination and axon calibre,
- accompanied by less extracellular free water,
- reduce diffusivity and increase fractional anisotropy (FA) in brain fiber tracts.

Lebel et al., Neuroimage 2008
N=202; age range: 5.6 - 29.2

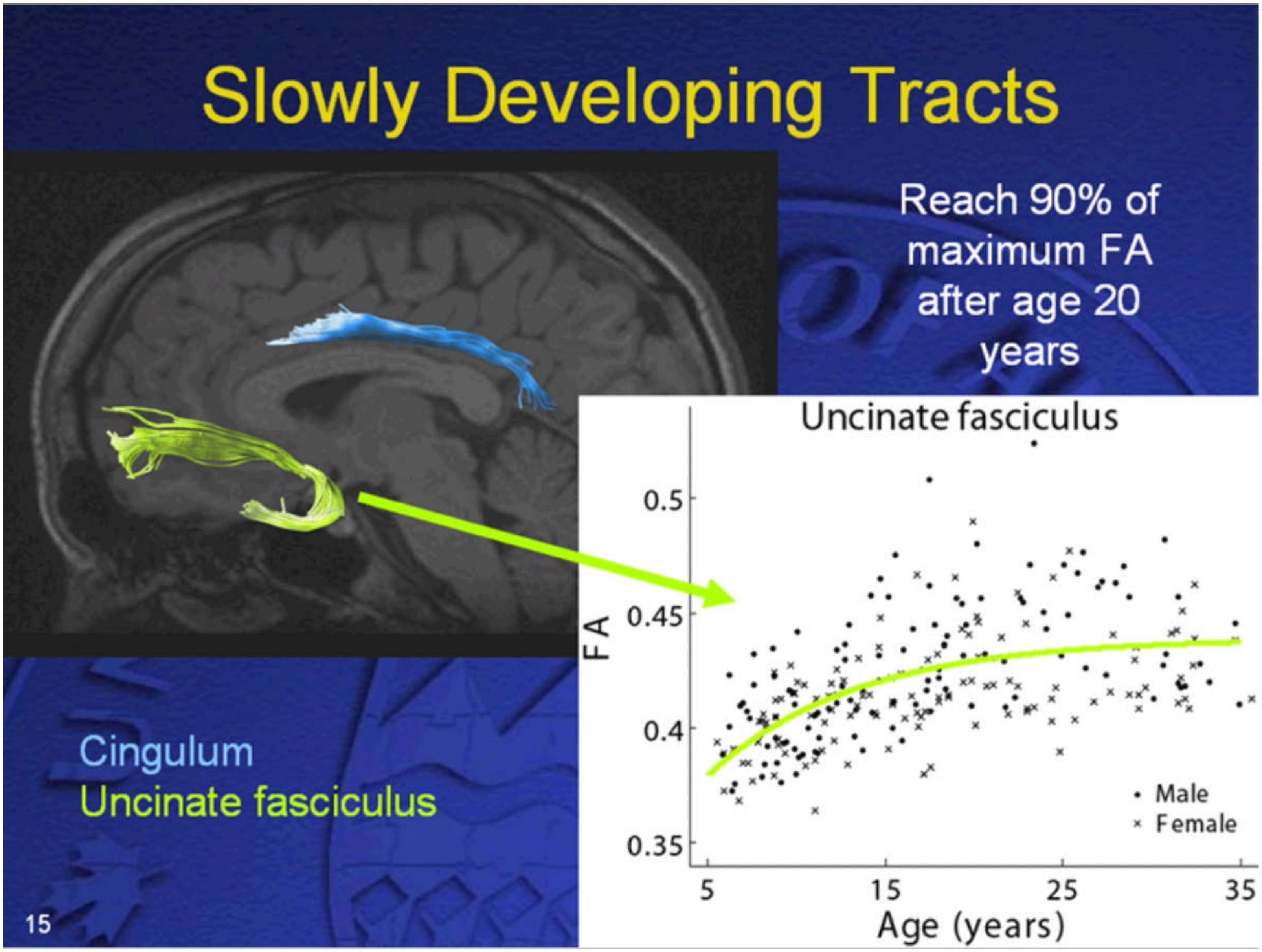




Lebel et al., 2007 ISMRM Meeting



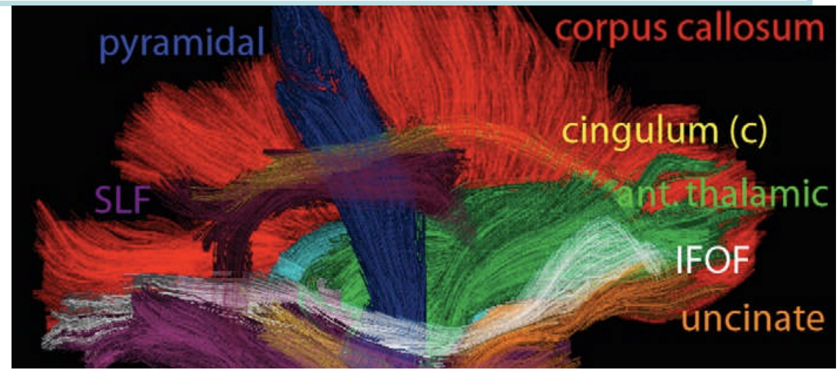
Lebel et al., 2007 ISMRM Meeting



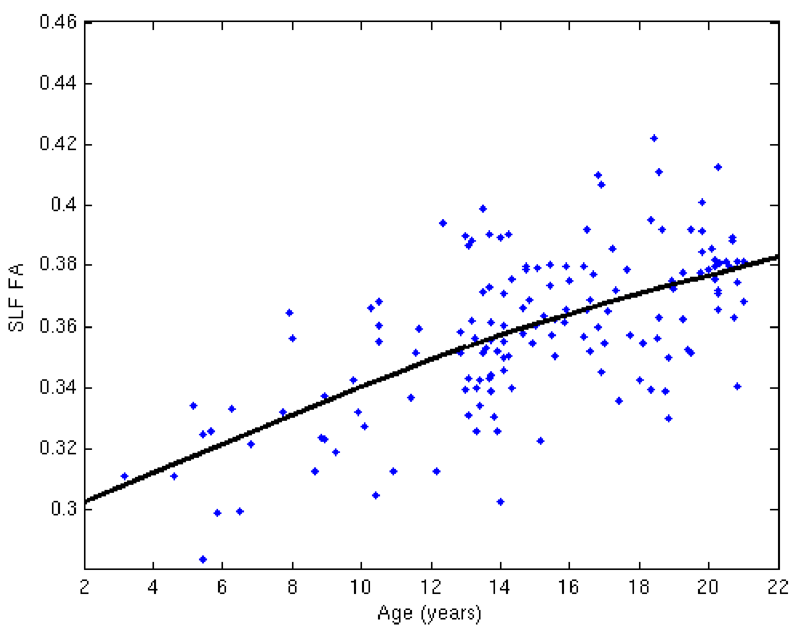
Lebel et al., 2007 ISMRM Meeting

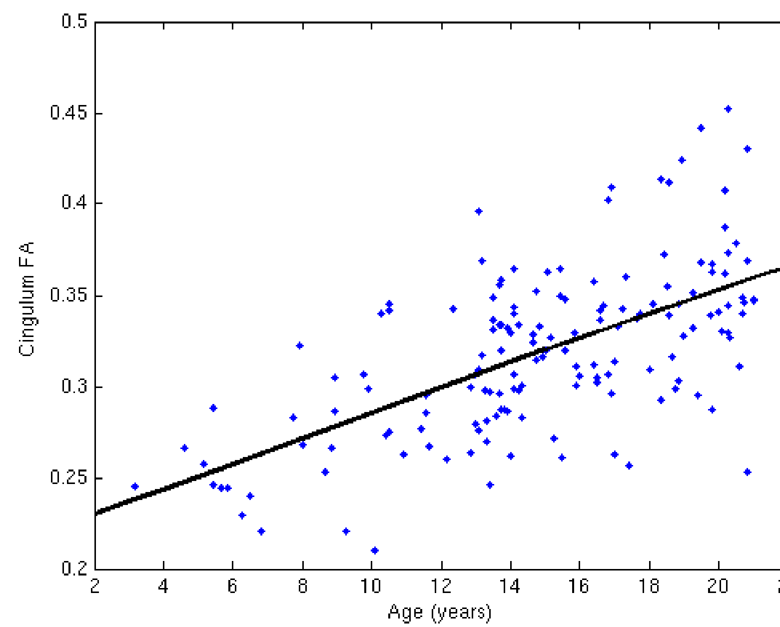
PING

Pediatric Imaging Neurocognition and Genetics



FA increases in superior longitudinal fasciculus and cingulum (ages 3 to 20)





Neural Architectural Variability

- Examined closely, the brain exhibits a complex pattern of age-associated tissue alterations well into adulthood.
- There is substantial variability among individuals at all ages.
- The questions:
  - What is the source of this variability?
    - Genetically-mediated difference in patterning of brain (cortical arealization, strength of connectivity, etc)?
    - Genetically-mediated status of maturation?
    - Experience-related neuroplastic effects (short term, long term)?
    - Interactions between experience and phase of maturation?
  - Is this variability functionally meaningful?

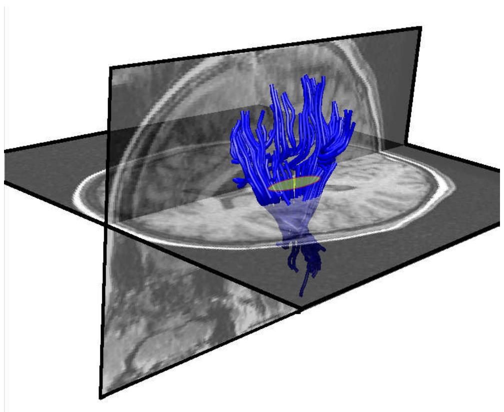
Variability in neural architecture is related to behavioral phenotypic differences, especially (but not exclusively) in children.

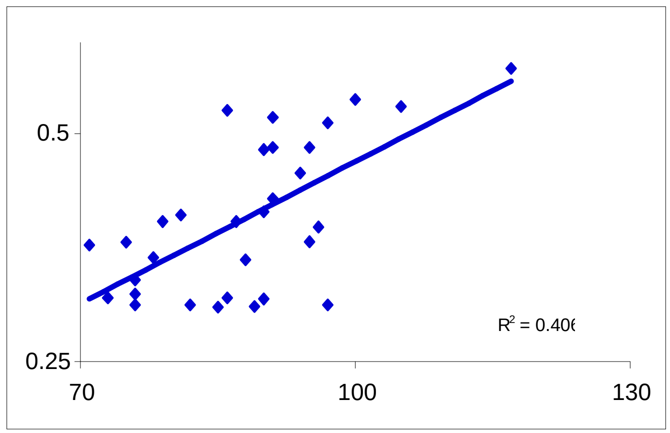
“Double Dissociation” in Correlation Patterns

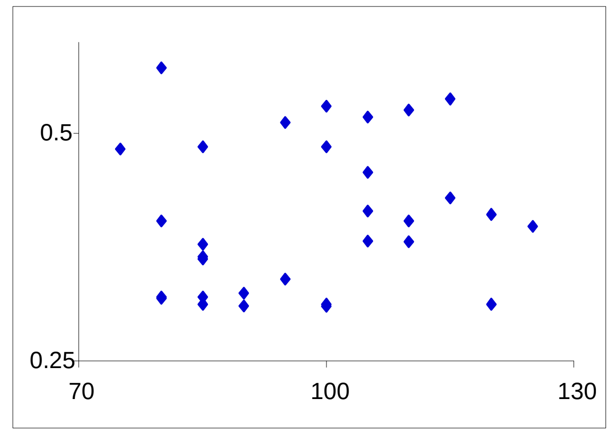
Standardized Word ID

Standardized Digit Recall

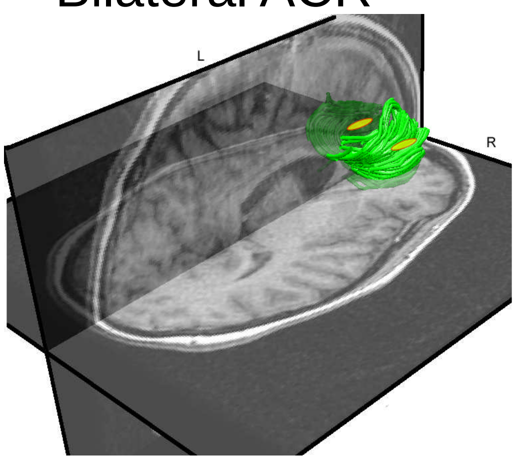
Left SCR

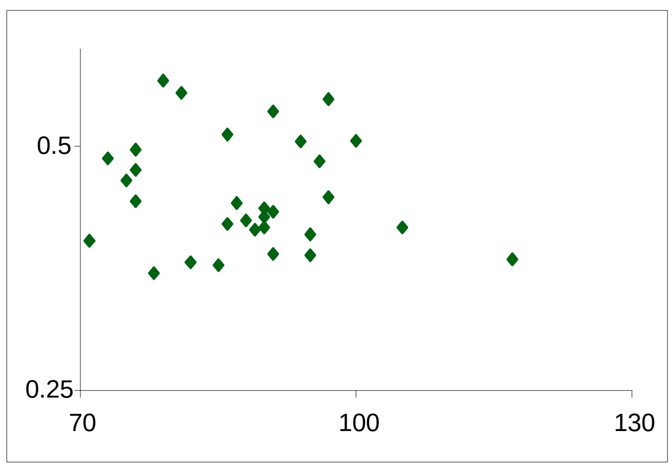


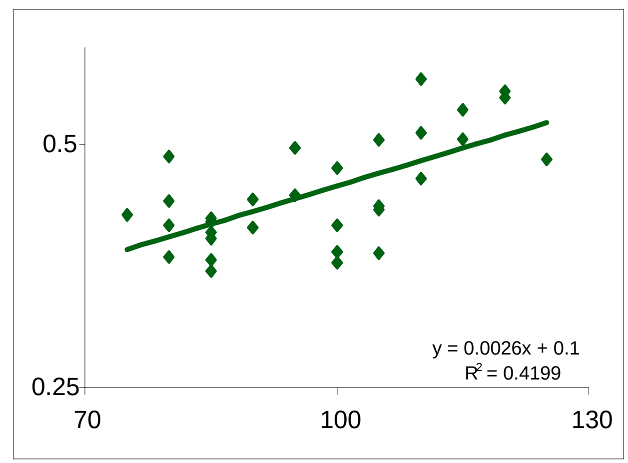




Bilateral ACR



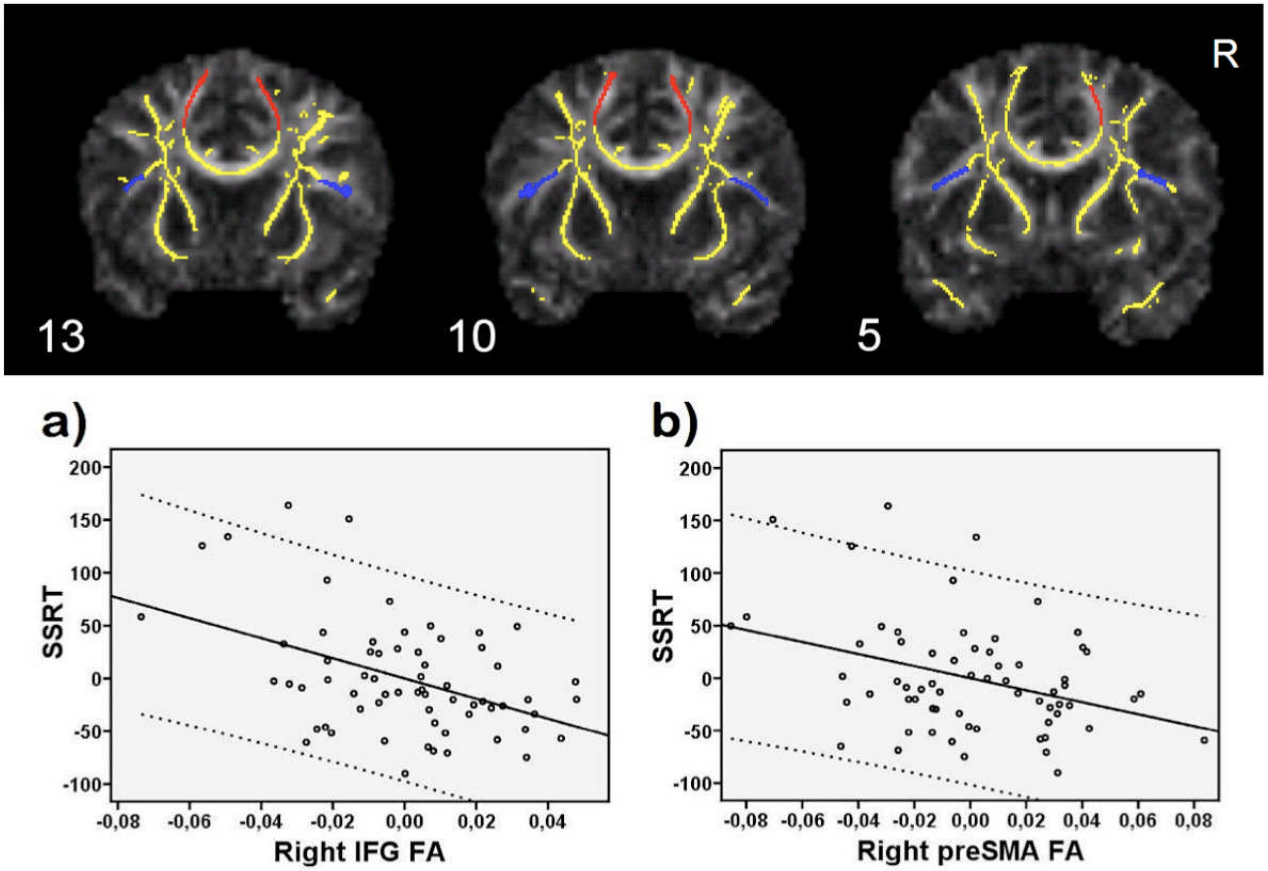




Niogi, S. & McCandliss, B.D.(2006) *Neuropsychologia*

FA in Right IFG and Right pre-SMA Both Contribute to Prediction of Inhibitory Function in Children

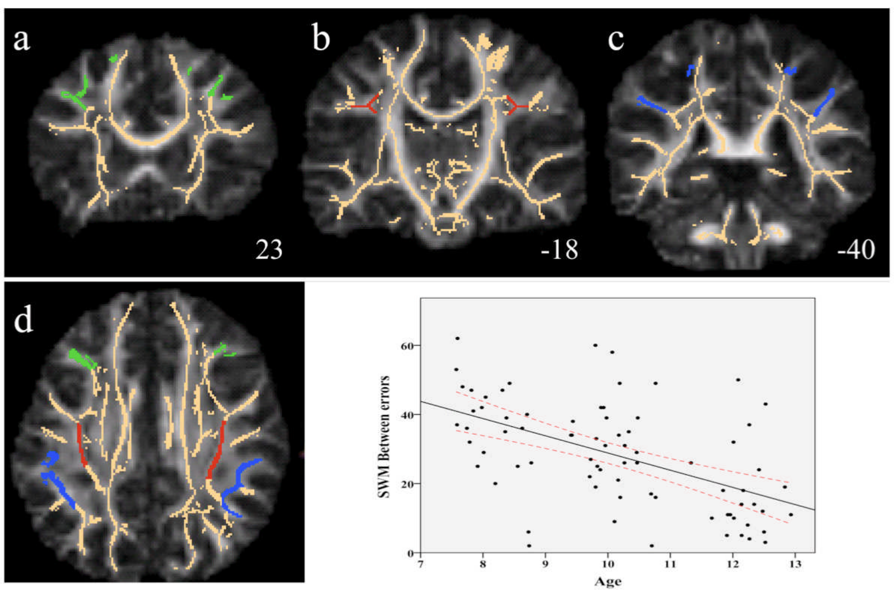
(Madsen SK, Baare WFC, Hansen MV, Skimminge A, Ejersbo LR, Ramsøy TZ, Gerlach C, Åkeson P, Paulson OB, Jernigan TL ., 2009, Neuropsychologia)

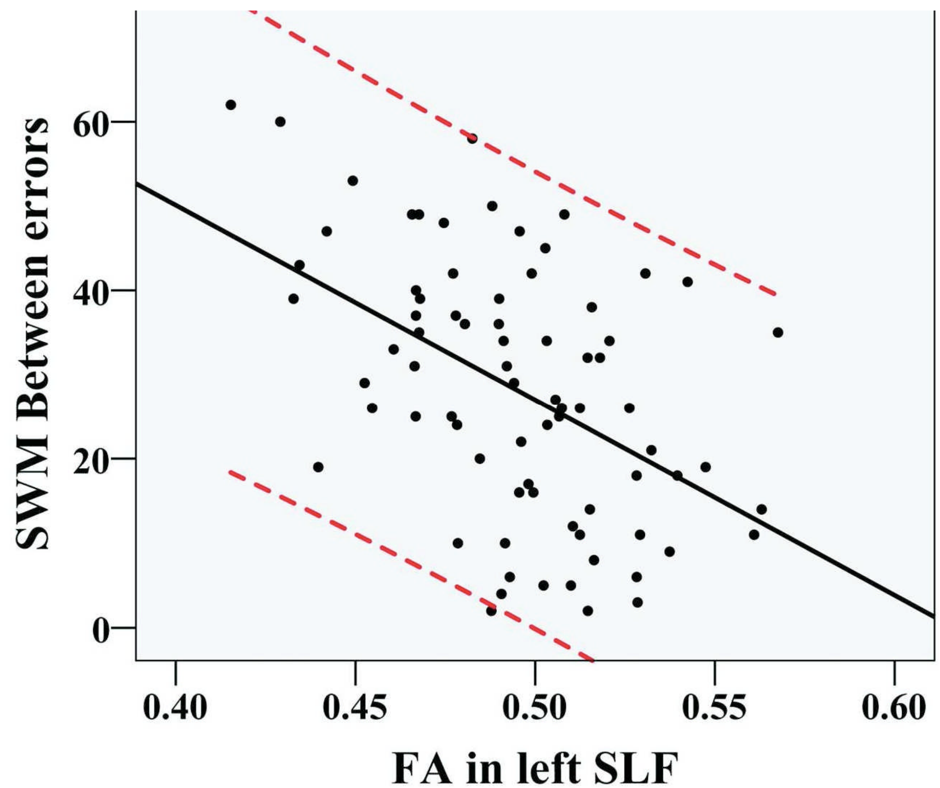


- Individual differences in children’s inhibitory function are related to FA differences within the neural circuit previously implicated in SST performance.

Spatial Working Memory Performance Related to FA in Superior Longitudinal Fasciculus

(Vestergaard M, Madsen KS, Baare WFC, Skimminge A, Ejersbo LR, Ramsøy TZ, Gerlach C, Åkeson P, Paulson OB, Jernigan TL. ., in press, J Cog Neuroscience)

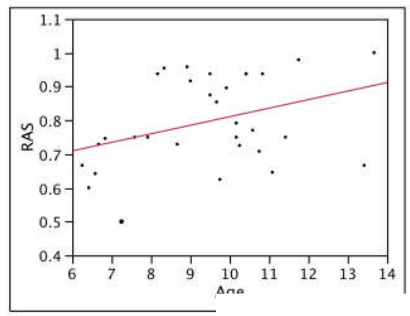


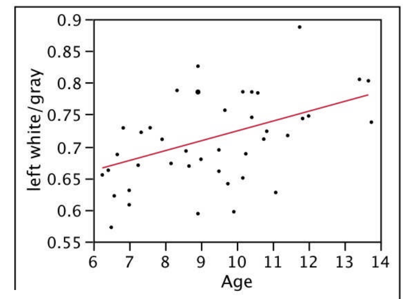


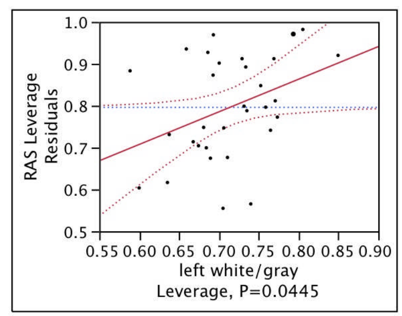
Temporal Dynamics of Learning Center

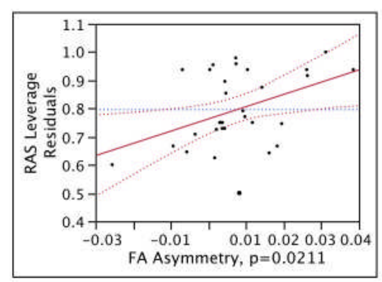
TDLC Study of Rapid Auditory Sequencing

- RAS improves and the white/gray ratio increases with age in children (6-13 years)
- Controlling for age, increased white/gray ratio is associated with better RAS.
- Higher left than right fiber tract asymmetries (in FA)are also predictive of better RAS.









Behavioral Variability is Related to Neural Variability
(particularly in brain connections)

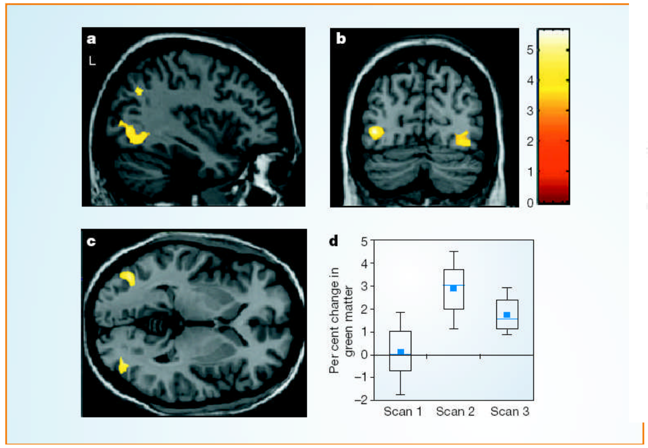
- Performance on cognitive tasks across multiple domains correlates with fiber tract structural characteristics.
- The associations remain after controlling for age and global parameters.
- It appears that profiles of behavioral attributes are reflected in profiles across brain fiber pathways.

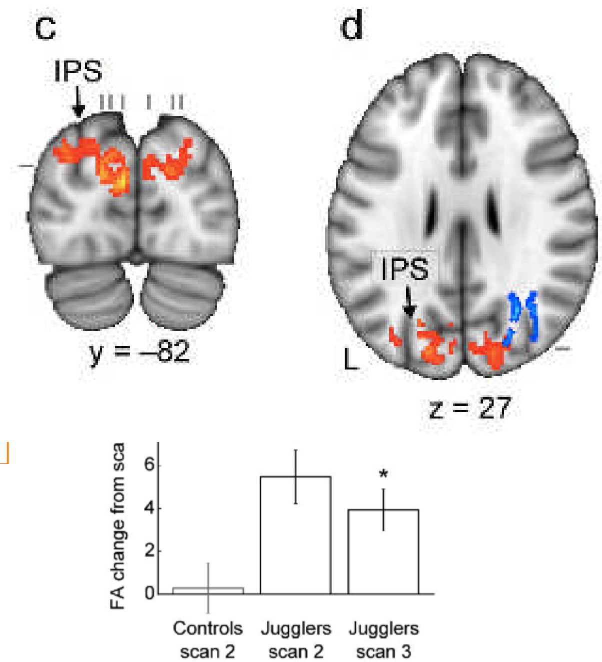
How do we interpret these associations between the neural and the behavioral differences?

- In children, could they arise because of differences (among children of similar age) in the pace of biological development of the brain?
- To what extent do they reflect functional effects of genetically-mediated differences in neural connectivity – or in the pace of development of these neural connections?
- To what extent are they driven by neuroplastic effects of experience, practice, training, and other factors that affect neural activity within brain systems?

Learning to Juggle Produces Change in Cortical and Tract Morphology

(Draganski et al., Nature, 2004; Scholz et al., 2009)

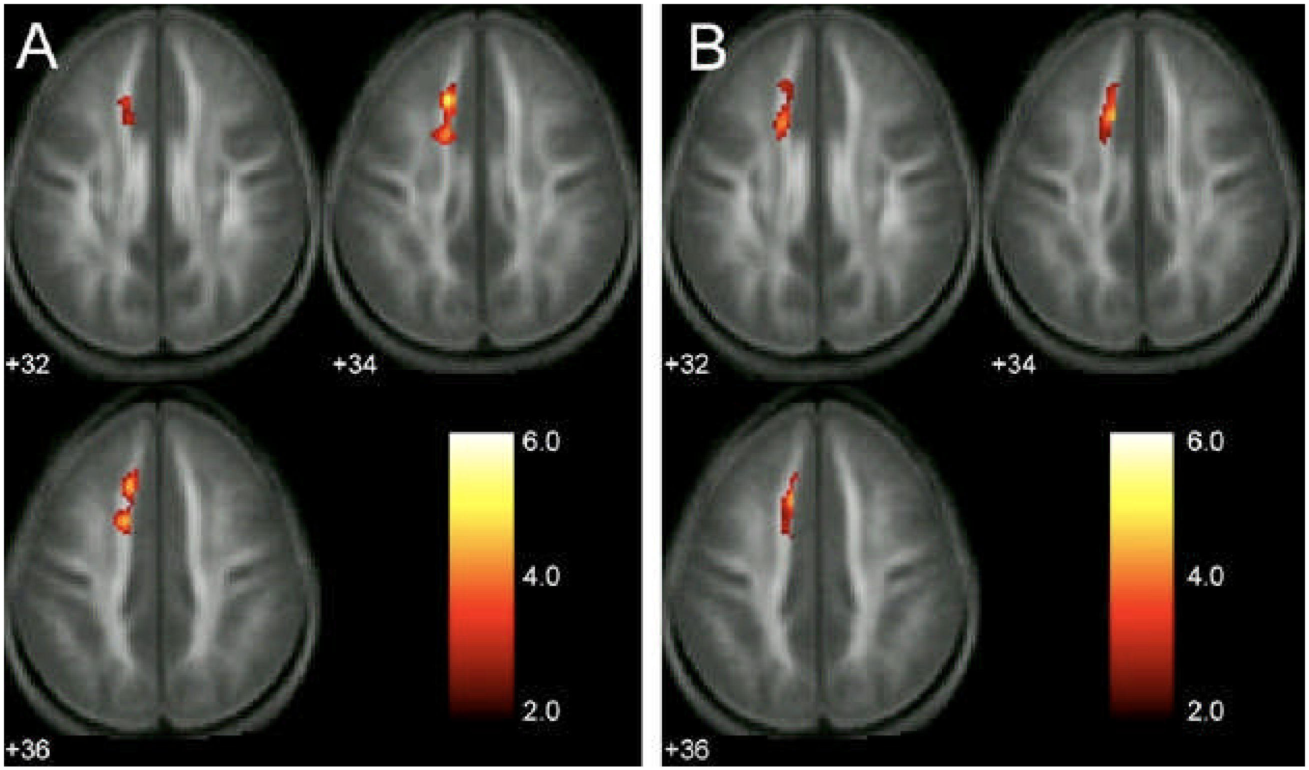




- Normal volunteers with no juggling skills were scanned at baseline.
- Subjects were taught a simple juggling task and re-scanned.
- After 3 months (Draganski et al.) or 4 week (Scholz et al.) without practice, jugglers were scanned a third time.
- Focal increases in gray matter were observed in middle temporal and left intraparietal sulcus areas, FA was increased in underlying white matter.

Altering Cortical Connectivity: Remediation-Induced Changes in the White Matter of Poor Readers

Timothy A. Keller and Marcel Adam Just, Neuron, 2009



A: Areas where FA increased in poor readers after remediation.

B: Areas where FA differed between good and poor readers at baseline

- 8-10 year old children show apparent intervention-linked alterations of FA in fiber tracts.

Training of Working Memory Impacts Structural Connectivity

Hikaru Takeuchi,[1] Atsushi Sekiguchi,[2] Yasuyuki Taki,[1] Satoru Yokoyama,[2] Yukihito Yomogida,[2,3] Nozomi Komuro,[4] Tohru Yamanouchi,[4] Shozo Suzuki,[4] and Ryuta Kawashima[1,2,5]

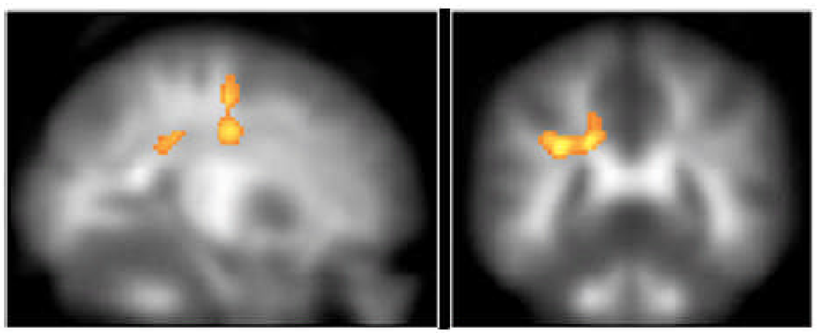
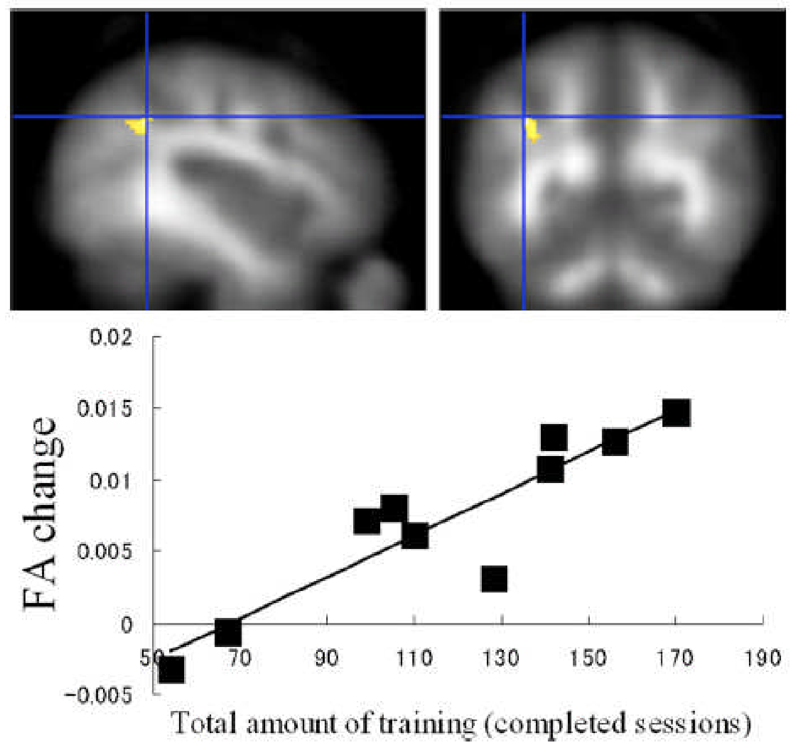


Figure 1. The cluster adjacent to the inferior parietal sulcus, which increased FA significantly after training, together with the significant cluster in the frontal lobe adjacent to the border between the frontal lobe and the parietal lobe ($p < 0.05$, after correction for multiple comparisons at cluster size, with a voxel-level cluster-determining threshold of $p < 0.005$ uncorrected).



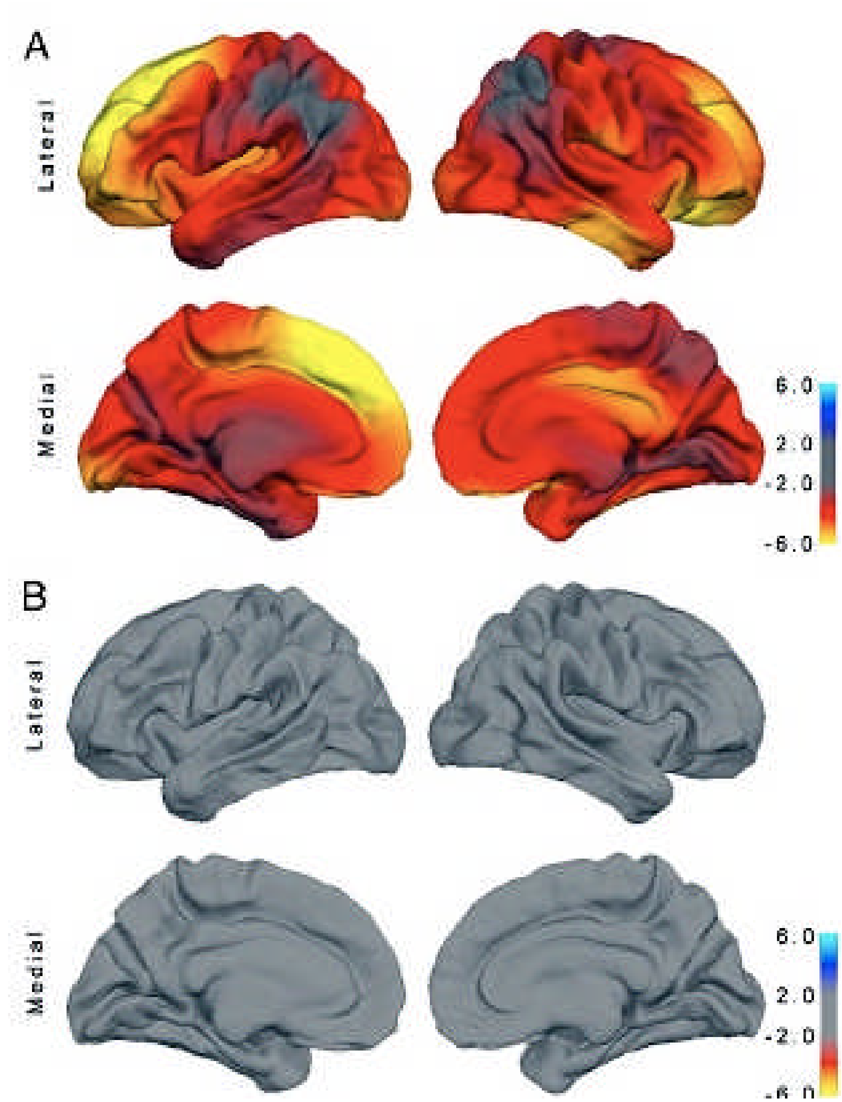
Genes Exert Strong Effects on Brain Morphology

- Twin studies have revealed high heritability of brain morphology.
  - We recently reported that 2 attributes of the neural architecture, cortical surface area and cortical thickness are both highly heritable, but exhibit no genetic association.

Sex-dependent association of common variants of microcephaly genes with brain structure

(Rimol et al., PNAS)

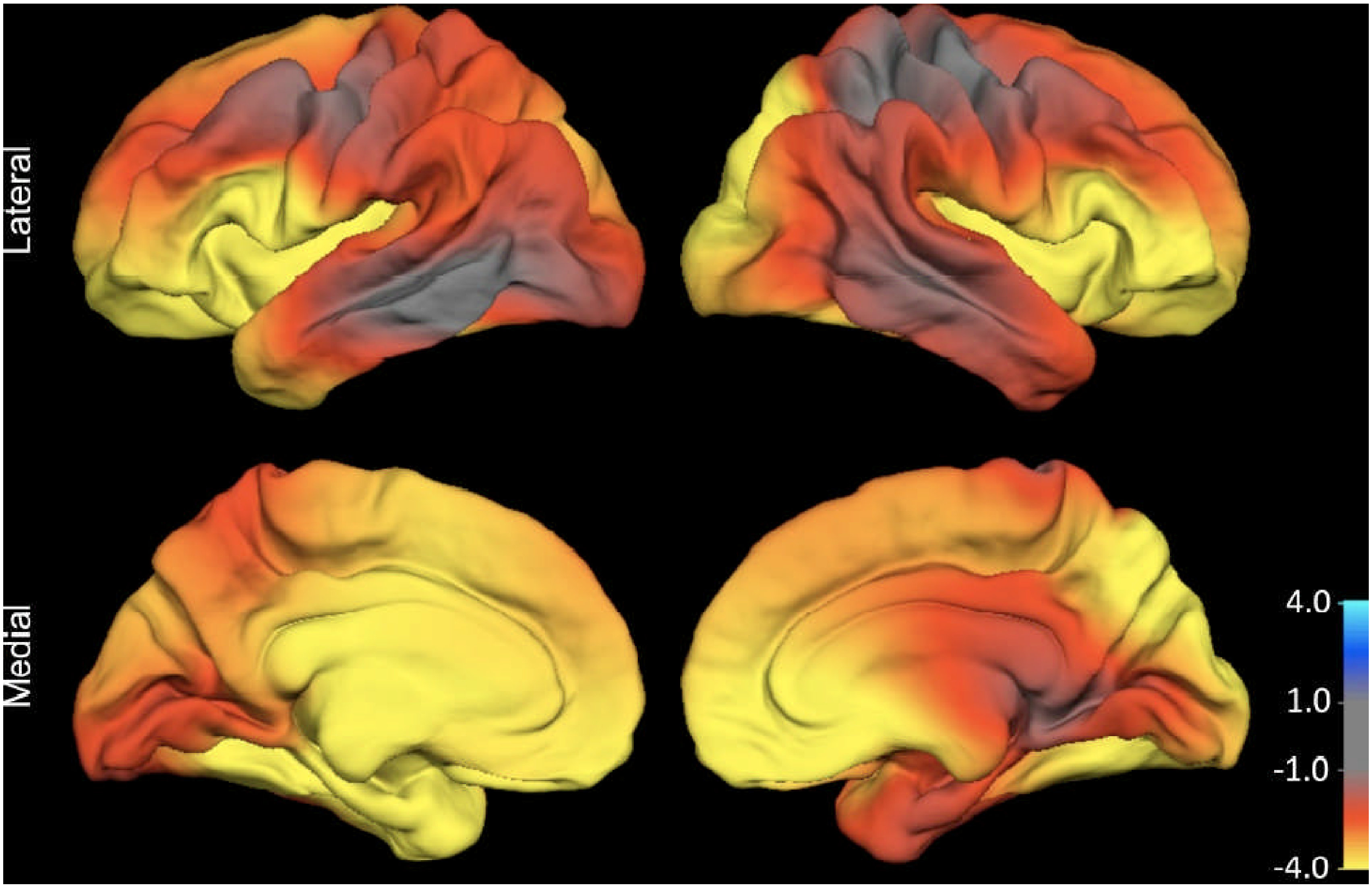
- Association of CDK5RAP2 SNP rs2282168 with cortical area in (A) males and (B) females.

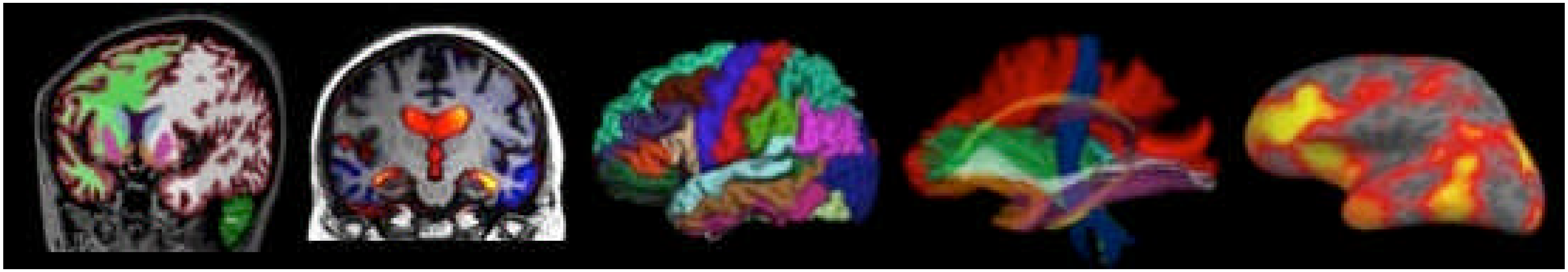


Pattern of Cortical Arealization Associated with Common Genetic Variation (in males)

MECP2 SNP rs2239464

(Joyner et al.,PNAS, 2009)





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Pediatric Imaging, Neurocognition, and Genetics

Creating a Pediatric Imaging Genomics Data Resource

- 9 sites across U.S.
- 1400 children, aged 3 – 20 years
- sMRI, DTI, rs fMRI
- Saliva samples for genotyping
- NIH Toolbox Cognitive Assessment

- A subset followed longitudinally at UCSD

Synergies with TDLC

- Studies of adaptive educational technologies within the Center cohort followed in longitudinal studies: to assess their impact on developing behavioral and neural phenotypes.
- Focus on collecting more information about social and emotional factors, both as modifiers of response to interventions, and as outcomes of them.

Why is this research relevant?

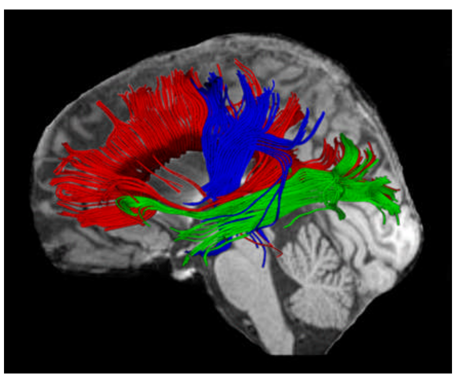
- Genetic variation almost certainly contributes to subtle differences in neural architecture that play a role in shaping the qualities of our minds.
- If this is true, then it is plausible that there are subtle qualitative differences among individuals in how they make sense of the world.
- Major advances in educational technologies have come from the application of adaptive, intelligent tutoring methods.

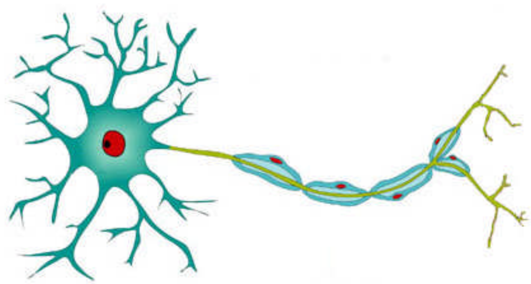
Why is this research relevant?

- The best adaptive technologies monitor the level of mastery of a learner and supply the most relevant information on an individual basis.
- But arguably, the most inclusive educational technologies require intelligence, not only about the learner at different stages of learning, but also about differences among learners.
- A more complete model of the nature and sources of variability in human learning is needed for the next generation of intelligent, adaptive educational technologies.

Acknowledgements

- NSF Temporal Dynamics of Learning Center
- UCSD Center for Human Development
- UCSD Multimodal Imaging Laboratory
- National Institutes of Health
- Danish Research Center for Magnetic Resonance, Copenhagen University
- Danish Medical Research Council
- Lundbeck Foundation





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Center for integrated molecular brain imaging

HUBU

DRC MR

Distributed practice over the long-term: Should spacing be expanding or equal interval?

Sean Kang

Department of Psychology, UCSD

NSF SLC Annual Meeting

15 October 2010

Acknowledgements

- National Science Foundation
- Institute of Education Sciences (US Department of Education)
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UCSD

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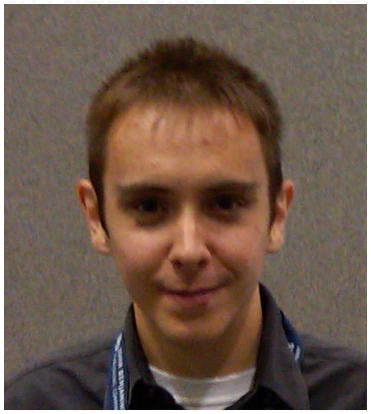
CU-Boulder



Rob Lindsey
CU-Boulder

The Spacing Effect

- Reviews are more effective when distributed or spaced out, rather than massed (with total time equated)

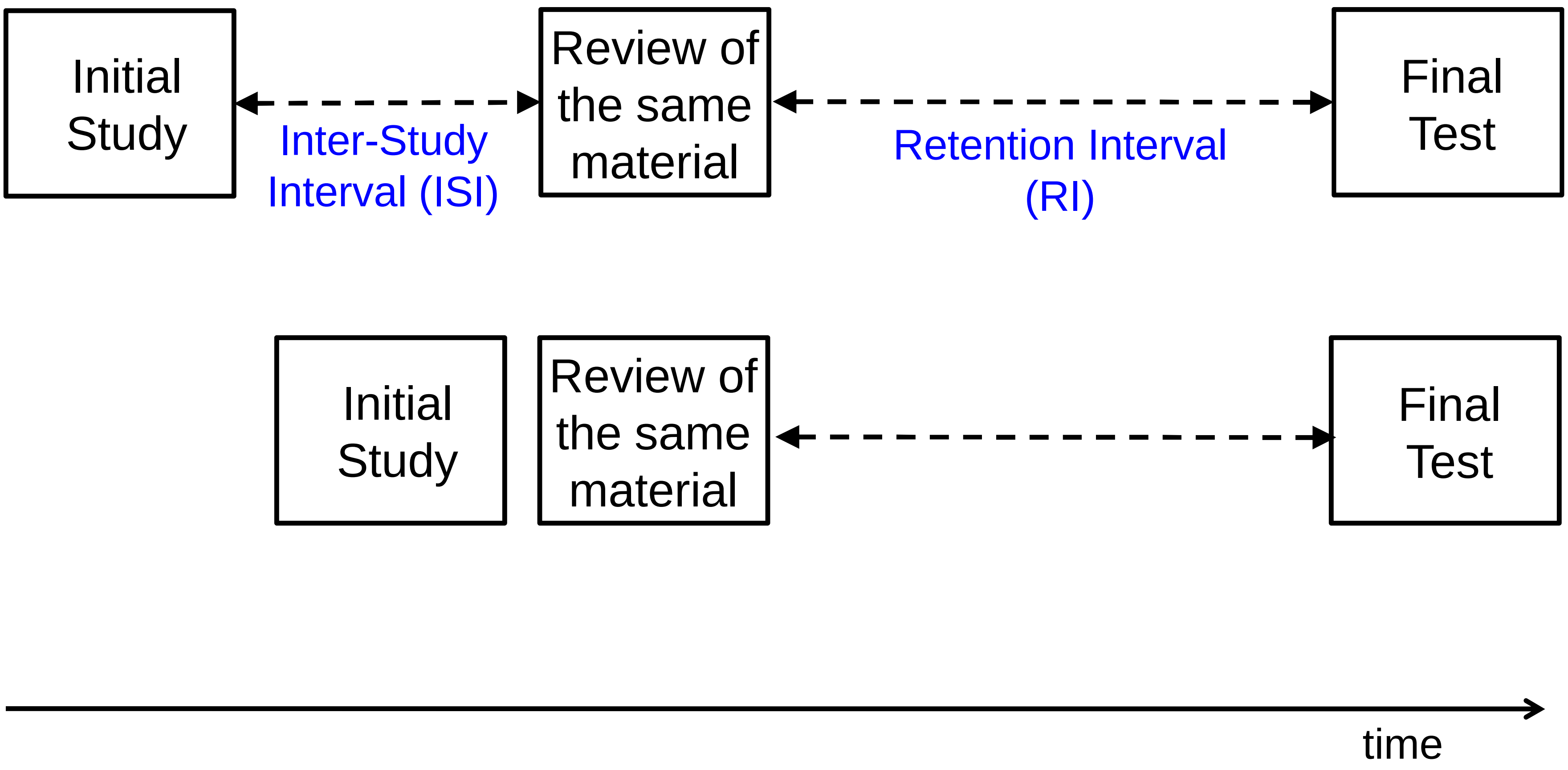
- One of the most robust phenomenon; observed with diverse range of materials / types of learning

- Ebbinghaus (1885):

  "…with any considerable number of repetitions a suitable distribution of them over a space of time is decidedly more advantageous than the massing of them at a single time."

The Spacing Effect

Basic structure of a study examining the effect of spacing:



The Spacing Effect

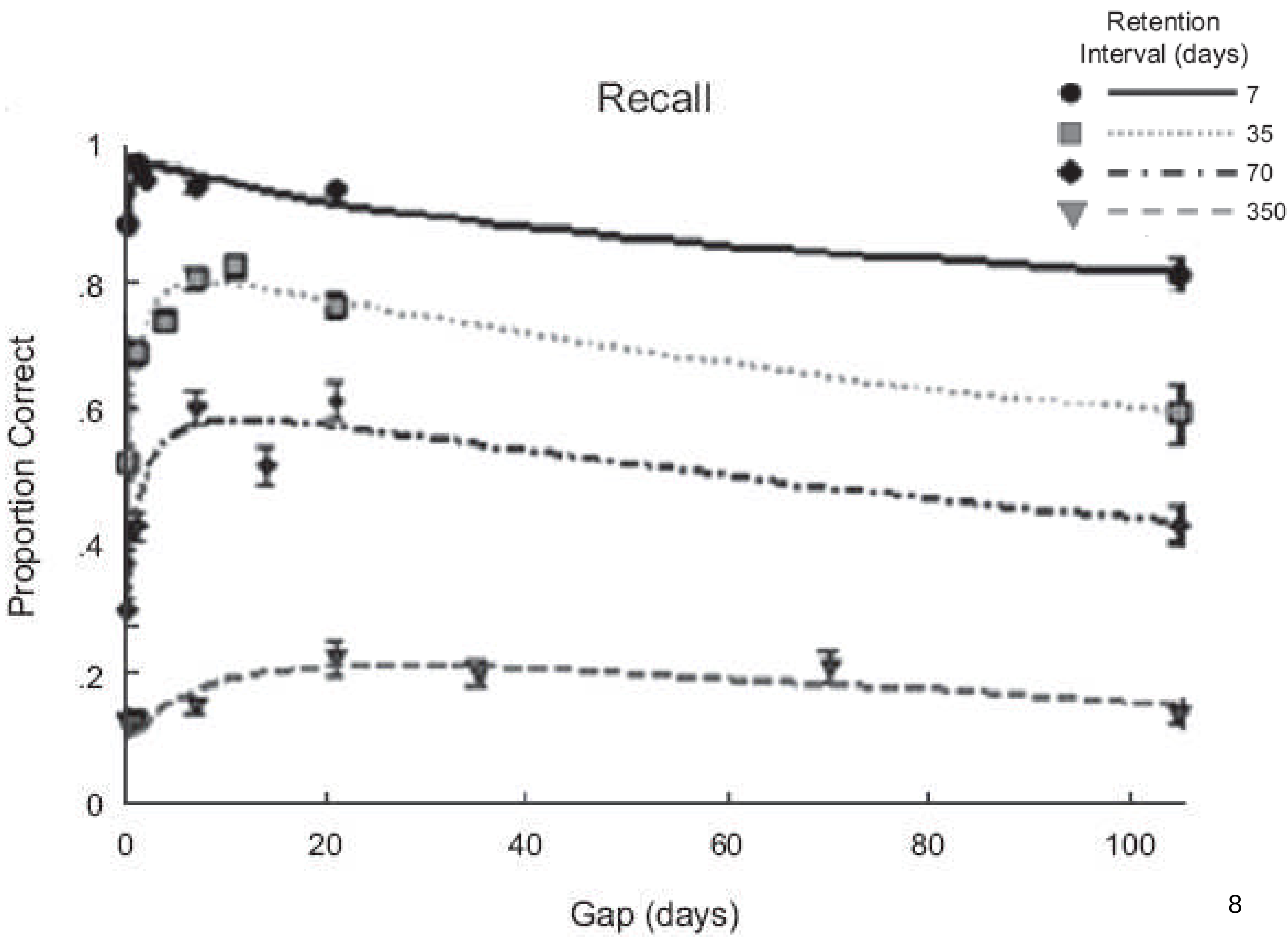
- Is there an optimal ISI?
- Does the answer depend on the RI?

Cepeda, Vul, Rohrer, Wixted, & Pashler (2008)

- Experimentally examined 26 different combinations of ISIs and RIs
- Stimuli: 32 obscure facts
- Procedure
  - Session 1: Learn 32 facts to criterion of one correct recall of each fact.
  - Session 2: After appropriate ISI, subjects tested 2x with feedback.
  - Session 3: After appropriate RI, final test.

Number of Subjects in Each Experimental Condition

Retention interval (days)	Gap (days)	Number of subjects
7	0	60
7	1	66
7	2	79
7	7	77
7	21	70
7	105	45
35	0	72
35	1	69
35	4	75
35	7	66
35	11	41
35	21	61
35	105	23
70	0	55
70	1	67
70	7	59
70	14	51
70	21	49
70	105	27
350	0	45
350	1	34
350	7	43
350	21	25
350	35	41
350	70	26
350	105	28

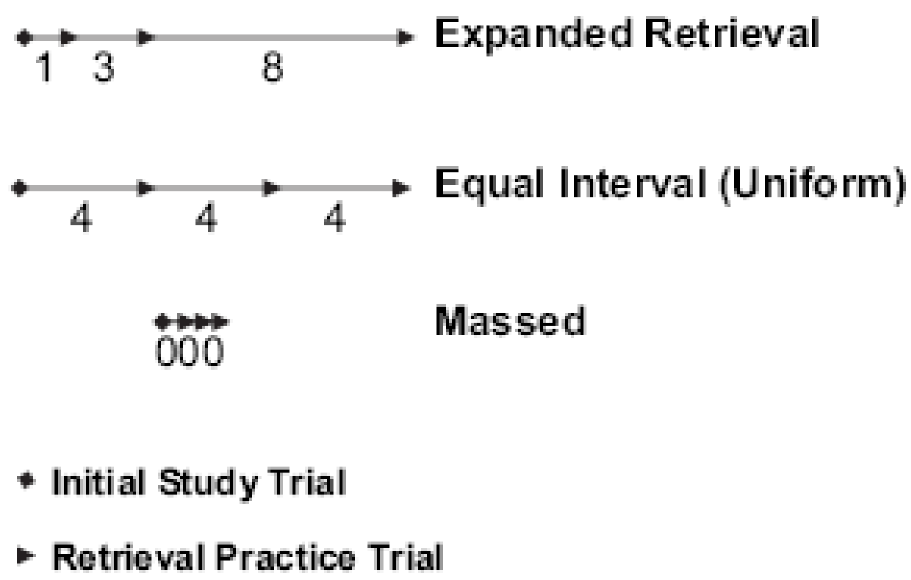

Recall
Retention Interval (days)
7
35
70
350
Proportion Correct
1
.8
.6
.4
.2
0
0
20
40
60
80
100
Gap (days)

Cepeda et al. (2008) - Conclusions

- Yes, there is an optimal ISI, but it depends on the RI.
- As RI increases, the optimal ISI also increases; the ratio of optimal ISI to RI is ~ 5-20%.
- The optimal ISI provided an average of a 64% increase in final recall, relative to the massed condition.

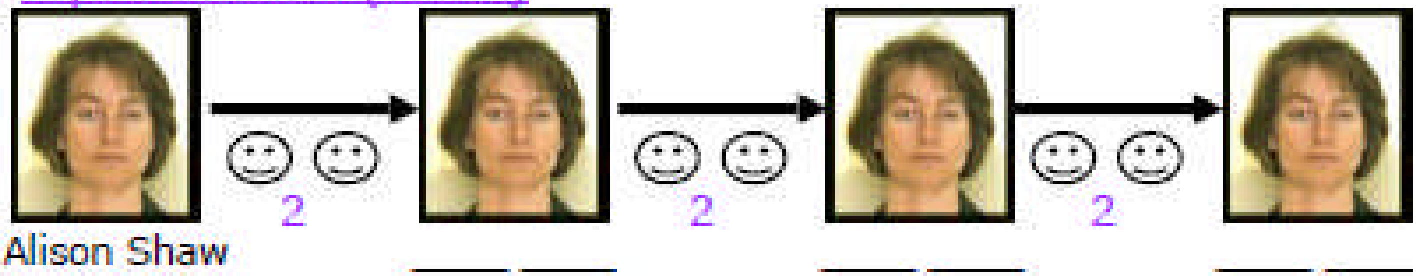
Expanding vs. Equal Interval Spaced Retrieval

FIGURE 1. A schematic diagram depicting examples of massed, equal interval and expanded retrieval practice schedules. The diamond represents the initial study trial, the line depicts the passing of time and number of intervening items, and each arrow point indicates a retrieval attempt.

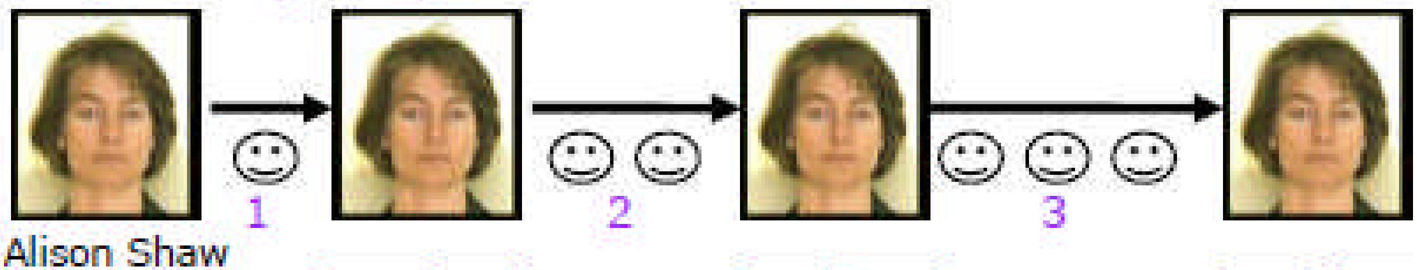


Equal Interval vs. Expanded Retrieval

Equal Interval (2-2-2)



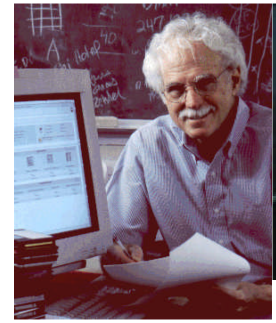
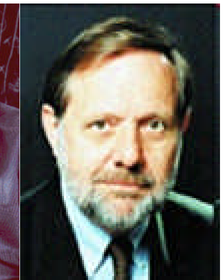
Expanded (1-2-3)



Same average spacing

Only the *distribution* of practice is different

Expanding vs. Equal Interval Spaced Retrieval

Landauer & Bjork (1978) proposed the advantage of expanding over equal interval retrieval practice.

Stimuli: 1st name – Last name pairs (e.g.,*John Smith*)	Retrieval attempt			Final recall (30 min later)
	1	2	3	
Expanded (1-4-10)	.61	.55	.50	.45
Equal interval (5-5-5)	.42	.42	.43	.40

An expanding retrieval schedule fosters successful retrieval at longer and longer intervals (i.e., by having the first retrieval attempt occur soon after studying, insures success; difficulty increases progressively with subsequent attempts).

But findings since then have been rather inconsistent, with several instances of failures to replicate.

E.g., Karpicke & Roediger (2007):

Final Recall in Experiment 1

Stimuli: GRE vocab
(*sobriquet – nickname*)

Learning condition	Retention interval 10 min	Retention interval 2 days
Massed (0–0–0)	.47 (.06)	.20 (.04)
Expanding (1–5–9)	.71 (.05)	.33 (.05)
Equal (5–5–5)	.62 (.07)	.45 (.05)
Single-immediate (1)	.65 (.05)	.22 (.04)
Single-delayed (5)	.57 (.06)	.30 (.04)

Note. Standard errors are in parentheses.

Other studies that failed to find an advantage of *expanding* over *equal interval* retrieval practice:

- Cull (2000)
- Carpenter & DeLosh (2005)
- Balota, Duchek, Sergent-Marshall, & Roediger (2006)
- Logan & Balota (2008)
- Karpicke & Roediger (2010)

Is Expanded Retrieval Practice a Superior Form of Spaced Retrieval? A Critical Review of the Extant Literature



DAVID A. BALOTA, JANET M DUCHEK, and JESSICA M. LOGAN (2007)

“The results of the current review lead us to conclude that, as expected, spaced practice produces considerable benefits in learning compared to massed practice; however, the additional benefits of expanded practice over equal interval practice have not been well substantiated in recent research.”

But…

Limitations of prior research comparing expanding and equal interval spacing:

1. Spacing almost always manipulated within a single learning session

2. Focus on final test performance after some specified retention interval

But…

In everyday practice, more realistic to think of review sessions occurring on separate days.

Also, what if the aim is to learn and maintain information over the long-term (rather than to optimise performance at a single time point in the future)?

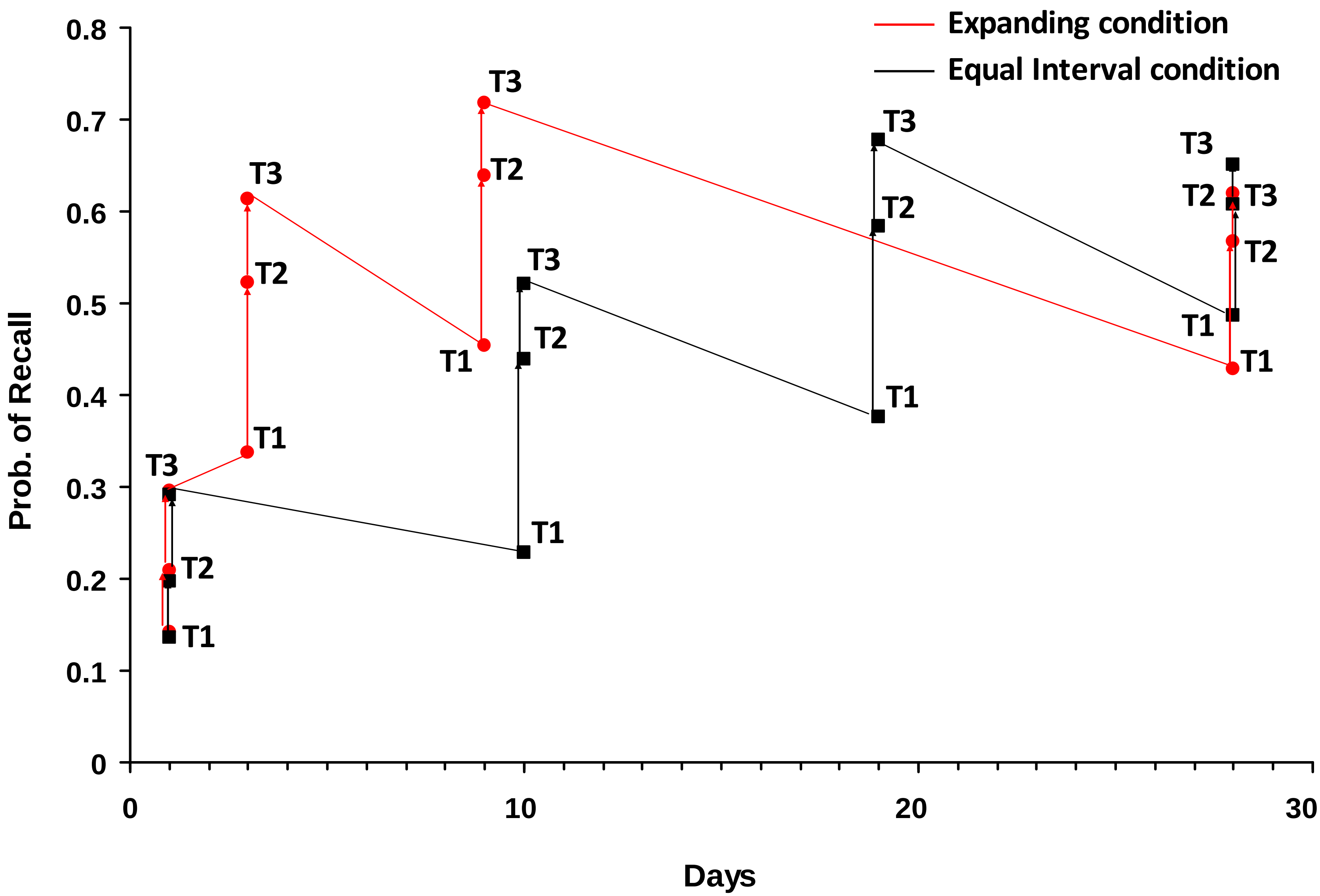
E.g., On-the-job training; medical training

Present study

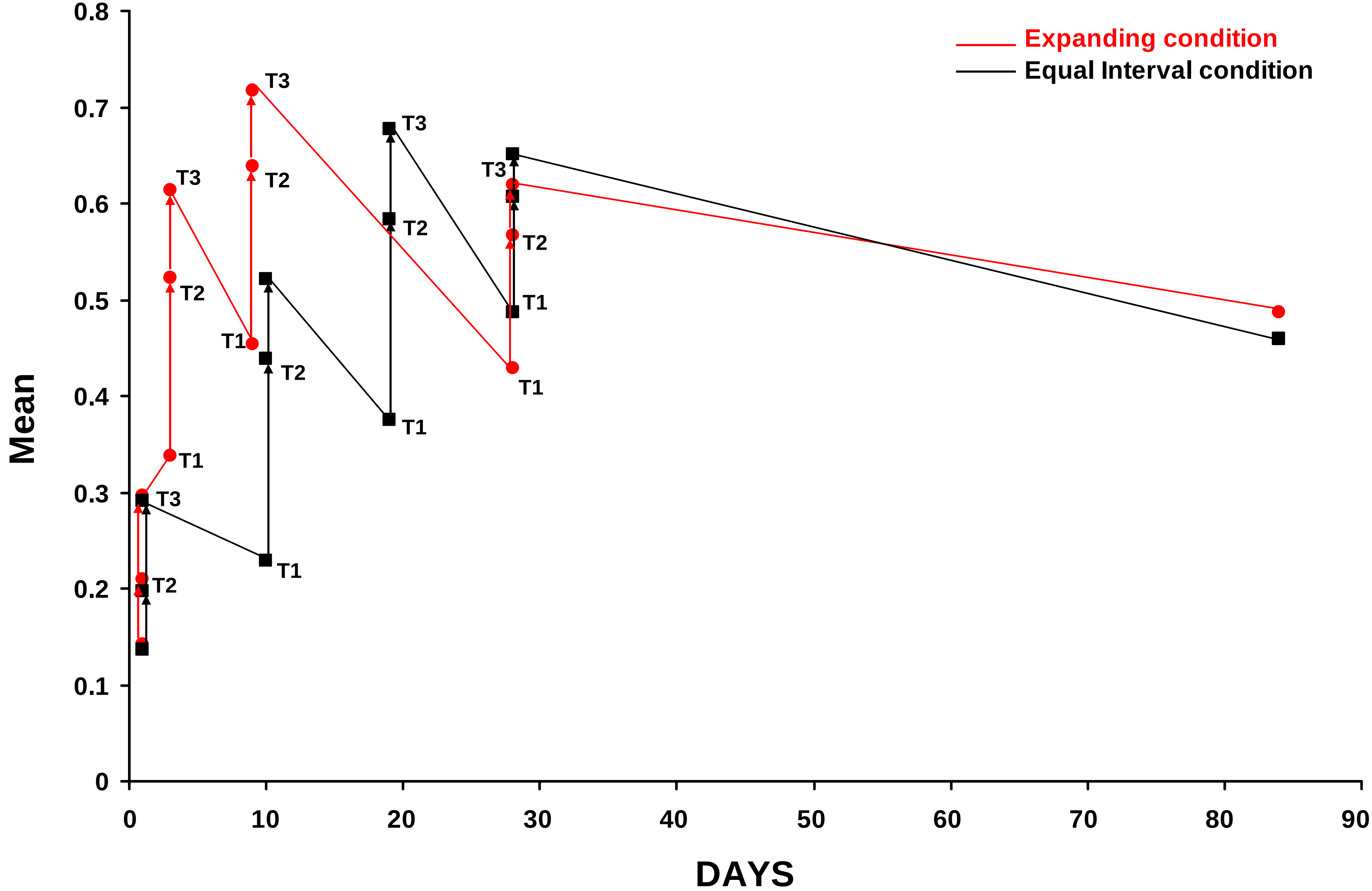
- Compared 2 different schedules of retrieval practice:
  - Expanding: Day 1, 3, 9, 28 (2-6-19)
  - Equal Interval: Day 1, 10, 19, 28 (9-9-9)
- Study stimuli: 60 Japanese-English word pairs
- Day 1:
  - Items presented once for Study (8s each), followed by 3 cycles of Test-Study (6s of cue only, followed by 2s of cue+target)
- Subsequent review days:
  - 3 cycles of Test-Study
- Final test on Day 84 (12 weeks after initial study)

Results

Performance during the training phase:



Results



Expanding condition
Equal Interval condition
Mean
DAYS
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
10
20
30
40
50
60
70
80
90
T1
T2
T3

Conclusions

- If review sessions are spread out over days, it is better to schedule the sessions over expanding intervals (rather than at equal intervals).
- Such an expanding schedule of practice seems to promote quicker acquisition of the information and better maintenance of the information over the learning period.
- In addition, an expanding schedule seems to retard forgetting of the information after a long delay.

Overview of VL2 Translational Research Program

Thomas E. Allen

2010 SLC PI Meeting

Setting a framework

- Inadequate history of classroom based research
- Science not at a point where we can specify pedagogical parameters. VL2 is the first time we have brought an interdisciplnary team of scientists together. Multidisciplinarity puts us at the ground floor of theory building.
- Characteristics of the landscape:
  - Low prevalence population
  - Highly diverse
  - Rabid proponents of opposing pedagogical philosophies.

VI2 framework

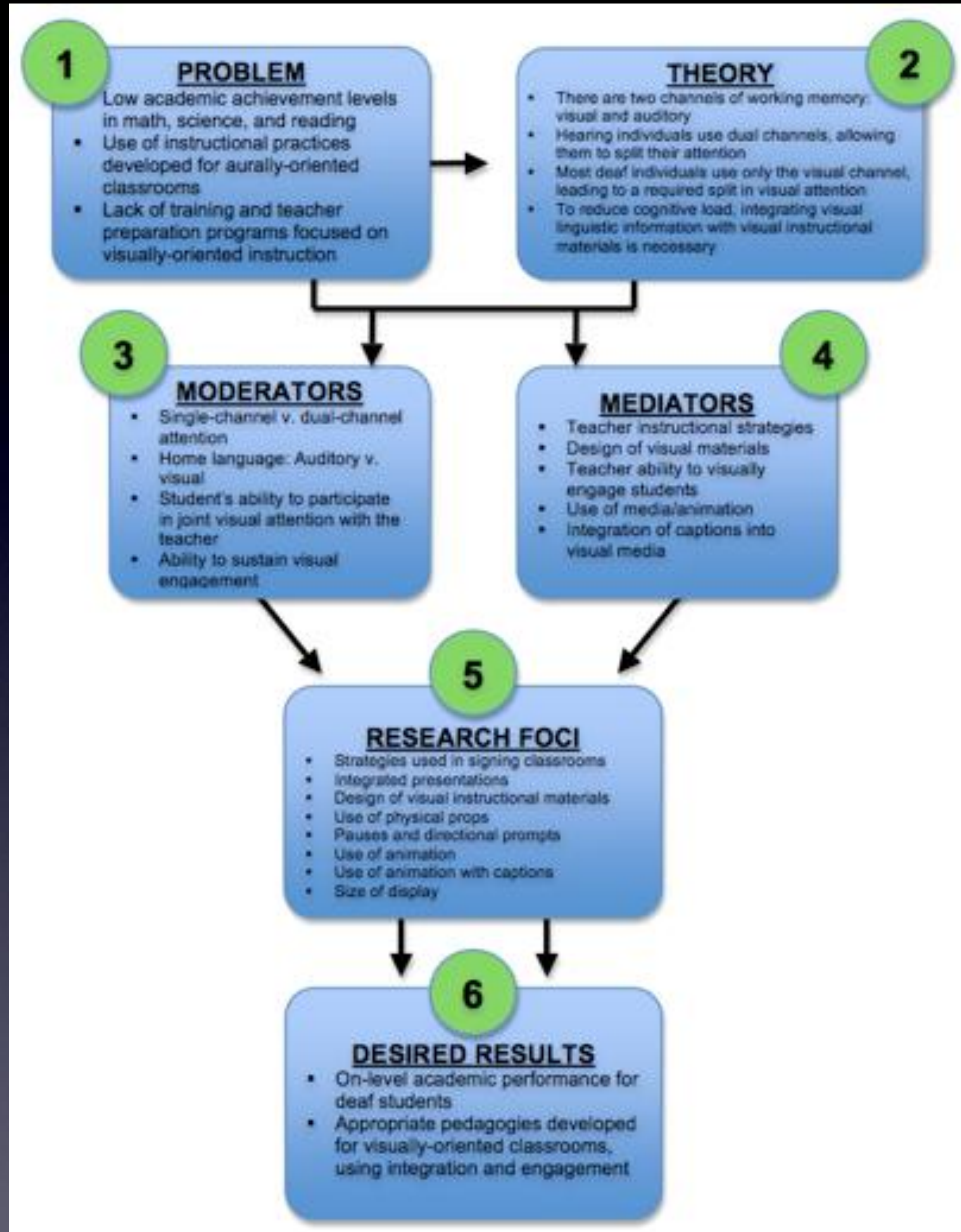
- Multiple pathways to success
- A difference model, not a deficit model
- Acknowledgement of individual differences
- Foundational work needed -
  - Creation of appropriate assessments.
  - Understanding Visual Language development
  - Studying population longitudinally
  - Identifying and evaluating promising instructional strategies
  - Designing in vivo experiments in classrooms based on our discoveries and emerging theory.

Three Research Thrusts

- Visual Attention
- Representation
- Combinatorial Competence

Visual Attention

- Visual engagement
- Eye gaze and eye shift
- Parental scaffolding
- Placement of objects in the visual space; allocation of perceptua resources in the periphery


1
PROBLEM
Low academic achievement levels in math, science, and reading
• Use of instructional practices developed for aurally-oriented classrooms
• Lack of training and teacher preparation programs focused on visually-oriented instruction
THEORY
2
• There are two channels of working memory: visual and auditory
• Hearing individuals use dual channels, allowing them to split their attention
• Most deaf individuals use only the visual channel, leading to a required split in visual attention
• To reduce cognitive load, integrating visual linguistic information with visual instructional materials is necessary
3
MODERATORS
• Single-channel v. dual-channel attention
• Home language: Auditory v. visual
• Student's ability to participate in joint visual attention with the teacher
• Ability to sustain visual engagement
4
MEDIATORS
• Teacher instructional strategies
• Design of visual materials
• Teacher ability to visually engage students
• Use of media/animation
• Integration of captions into visual media
5
RESEARCH FOCI
• Strategies used in signing classrooms
• Integrated presentations
• Design of visual instructional materials
• Use of physical props
• Pauses and directional prompts
• Use of animation
• Use of animation with captions
• Size of display
6
DESIRED RESULTS
• On-level academic performance for deaf students
• Appropriate pedagogies developed for visually-oriented classrooms, using integration and engagement

Problem

- Low academic achievement levels in math, science, and reading
- Use of instructional practices developed for aurally-oriented classrooms
- Lack of training or teacher preparation programs focused on visually-oriented instruction.

Theory

- Two channels for working memory: visual and auditory.
- Hearing individuals use dual channels allowing them to split their attention
- Most deaf individuals use only the visual channel, requiring continual shifting of attention
- To reduce cognitive load, integration of the language of instruction with instructional materials is necessary.

Moderators

- Single channel versus dual channel for attention
- Home language: auditory versus visual
- Capacity for joint visual attention
- Ability for sustained visual attention
- Temporal and spatial aspects of attention

Mediators (Malleable factors)

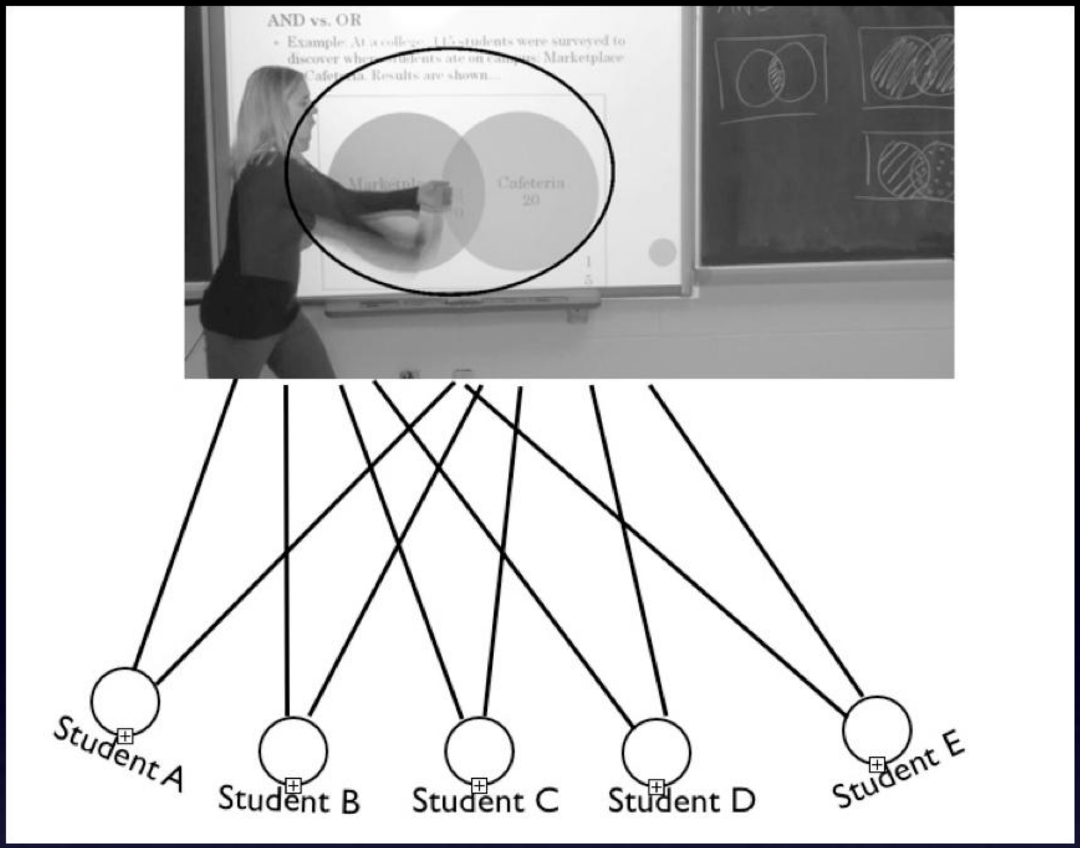
- Teacher instructional strategies
- Design of visual materials
- Management of visual attention
- Classroom arrangements

Possible research focci

- Bilingual strategies in signing classrooms
- Instructional material design elements
- Use of physical props
- Pausing and directional prompts
- Animation
- Animation with captions/fingerspelling
- Size of display

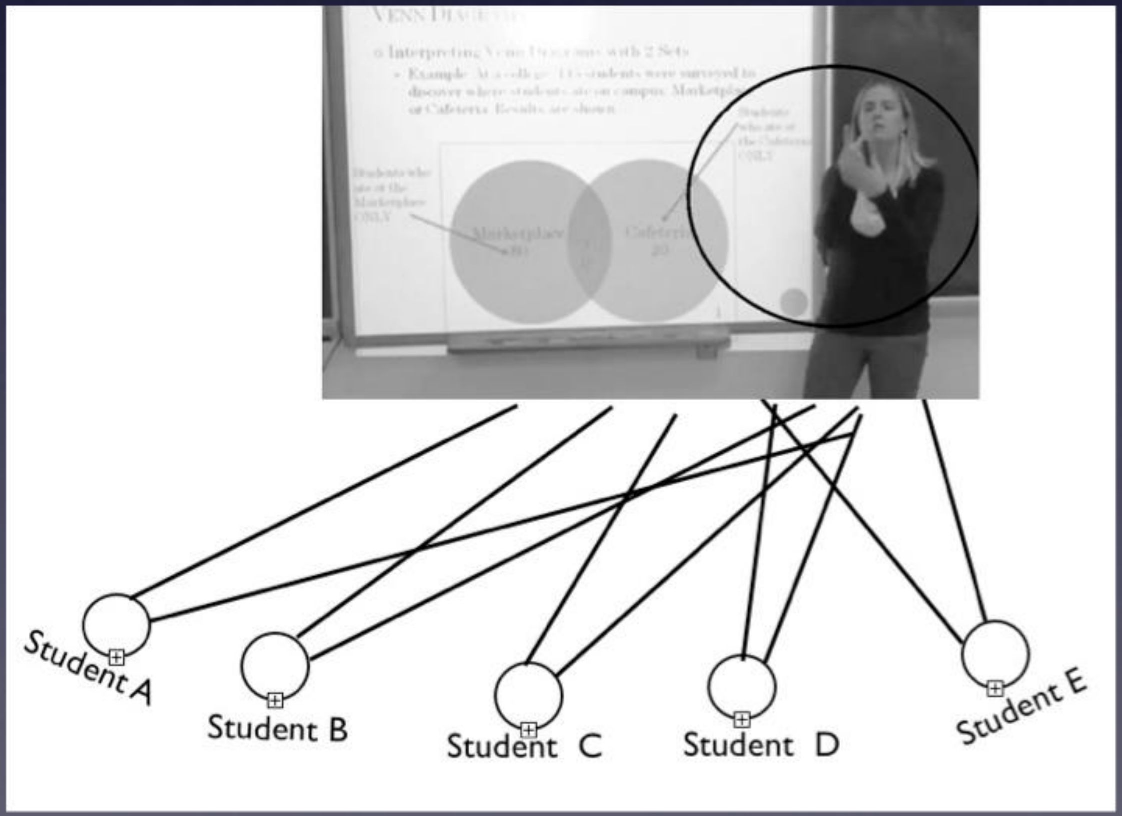
Desired results

- On-level academic performance
- New pedagogies developed for visually-oriented classrooms that integrate visual language with visual displays and ensure effective management of visual engagement.



Integration of sign and diagram

- Position of students and teacher
- Position of the hands
- Use of PowerPoint
- Pausing rules
- Embedded video on the same display



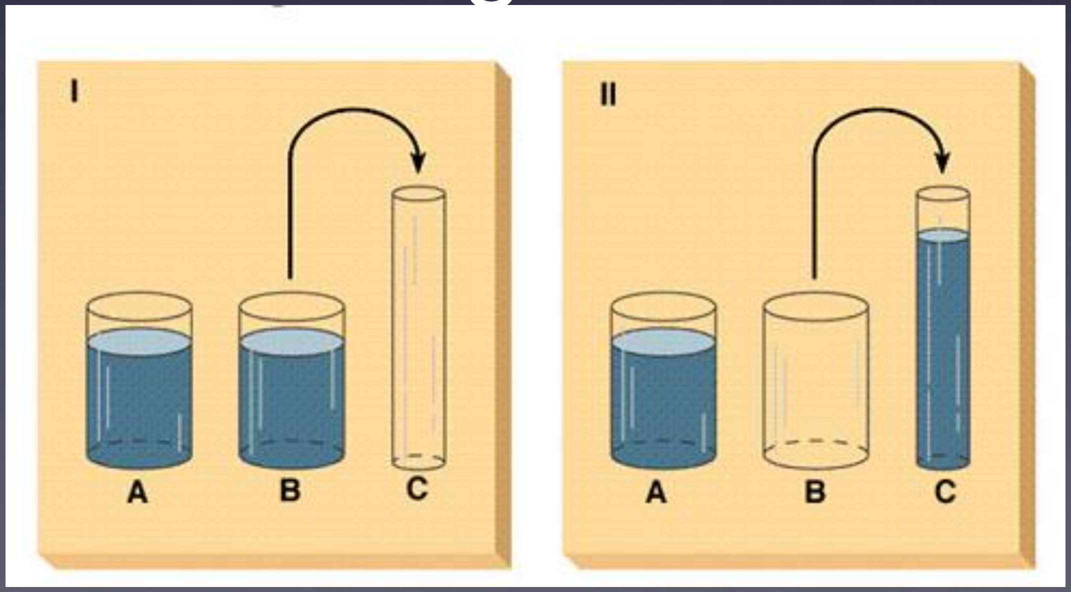
Separation of sign and diagram

Representation

- How are complex relationships depicted?
- Embodiment of meaning: human body as an instructional media
- Role of gesture?

Example:

- Padden and Goldin Meadow study:
  - Properties of conservation and concepts of mathematical equivalenceand use of gesture in learning



Combinatorial Competence

- Mapping linguistic elements across modalities
  - Lexical access in two languages
- Language experience versus phonological knowledge
- Coding strategies for English print for signing children

Classroom studies

- A focus on bilingual approaches
- Identification of promising existing strategies.
- Apply rigorous assessment and progress monitoring approaches.
- Conduct classroom based research with a view towards conducting more controlled experiments.

Population and Assessment Studies

- Early Education Longitudinal Study (EELS)
- Broad range of assessments, including newly developed assessments
- Broad sample
- Identification of factors that contribute to reading gains.

The VL2 Early Education Longitudinal Study (VL2 EELS):

Identifying factors influencing early literacy for deaf students through longitudinal study of student, family, and school characteristics

Donna A. Morere, Ph.D
Gallaudet University
VL2

Problem: Inadequate Reading Achievement in Deaf Children

- Average reading levels for 18 YO's for 1990 SAT-8 Reading Comprehension (Holt, J., 1993):
  - 3.8 grade level for profoundly deaf students
  - 4.5 grade level for severe hearing loss
  - 5.4 grade level for those with less than severe loss
  - All levels combined averaged about grade 4.5.
- Despite various interventions, 1997 Stanford 9 data continue to show 3rd to 4th grade reading comprehension for D/HOH 18 YO's. (Traxler, 2000).
- **These findings are essentially unchanged from the results of surveys in the early 1970's**.

Deaf Readers

- Only 40% of college students with severe to profound hearing losses read at or above the fourth grade level and about eight percent read at or above the eighth grade level. (Allen, 1994).

- We need to understand what is required for deaf children learn to read in order to improve these results.

Learning to Read

- Reading is not a "naturally developing" process
  - Print is an artificial symbol system typically mapped to spoken language.
  - Regardless of hearing status, reading is an artificial skill which must be taught.
  - Up to 40% of hearing children have trouble learning to reading.
    - Intelligence does not determine reading skill.

Reading & Language

- Learning to read depends on the child's existing knowledge of language
- For hearing children this is typically the language in which they will learn to read.
- Deaf children may communicate using
  - The language of print or communication methods based on that language
    - Oral or Cued English - PMSG
    - English-based signs - ~M, SG
  - A language different from the language of print
    - American Sign Language - different PMSG

Research: Adult deaf readers

- Some studies indicate that good deaf readers use a phonological decoding
  - Hanson, 1989; Hanson, Goodell & Perfetti, 1991
- Some indicate that D/HOH readers depend heavily on context (Marschark & Harris, 1996)
  - Others suggest that this strategy is inadequate for poor deaf readers (deVilliers & Pomerantz, 1992).
- Reading comprehension appears to depend on the range and depth of word knowledge of the reader. (Paul, 1996)

Research: young deaf readers

- Research into the reading skill development of deaf children is limited, and typically relates to subsets of deaf children, such as
  - Those with cochlear implants (Geers, 2003)
  - Those using forms of communication
    - Signed English, Total Communication, Cued Speech, Oral, ASL
      - Luetke-Stahlman & Nielson (2003); Dyer, MacSweeney, Szczerbinski, Green & Campbell (2003); Charlier & Laybaert (2000)

Research: young deaf readers

- Other research has focused on specific approaches to single word decoding:
  - phonetic
  - sign- based
  - print-based (orthographic)
  - fingerspelling
    - Alegria, Lechat, & Leybaert, 1990; Bellugi, Klima & Siple, 1975; Hanson, 1982; Perfetti & Sandak, 2000; Poizner, Bellugi & Tweeney, 1981; Shand, 1982; Miller, 2006; Haptonstall-Nykaza & Schick, 2007

Intervention research with deaf readers

- Limited and typically focus on development of skills associated with reading in hearing children
  - Targeted interventions for phonetic decoding
    - Visual phonics (Narr, 2008; Trezek & Malmgren, 2005; Trezek and Wang, 2006)
    - Despite apparent gains in rhyme judgment and, presumably, decoding, Narr reported
      - “Results did not support a relationship between reading ability and rhyme judgment for these students.” (p.413).

Very little attention has been paid to reading skills beyond the decoding process.

The assumption appears to be that once a child can decode, s/he can read for comprehension.

Implications for intervention

- Recommendations concerning interventions and program changes have been based on
  - Philosophical positions
  - Assumptions based on reviews of the literature on deaf and hearing readers
    - Support for a combination of full language access via ASL plus “limited access” to spoken language (Perfetti & Sandak, 2000)
    - Support for bilingual ASL/English via Cued Speech (LaSasso & Metzger, 1998)

How can we enhance reading development in deaf children?

- Research on existing reading skills of adults and children does not tell us what is required to *develop* these skills.
- In order to determine what is needed for children to develop reading skills, we need to look at how these skills develop.
    - Language (through all modalities)
    - Reading
- This is the objective of the VL2 EELS.

Sample

- A cohort of 3, 4, and 5 year olds
- Broad range of communication:
  - Oral, Total Communication, Cued Speech, ASL/English bilingual
- Varying educational settings:
  - Residential/day SFD, self contained in mainstream, mainstream/reverse mainstream
- Who use/don’t use HA/CI
- Broad ranges of skills
- To be followed for 3 years

Assessment

- Questionnaires completed by school administrators, teachers, and parents
  - Program, teacher, and parent attitudes about communication and teaching deaf children
  - Characteristics of the educational program
    - Communication style, class size, teacher background & communication, etc.
  - Characteristics of the home
    - Communication used, discipline, literacy focus, etc.
  - Characteristics of the child

Assessment

- Cognitive functioning
- Cognitive processes associated with reading
- Language (English and ASL)
  - Test administration will be matched to the child’s communication
  - Vocabulary and “listening” comprehension
- Basic reading and pre-reading skills

Direct Assessment of the Child

- Cognitive level
  - PTONI
- Attention
  - Leiter-R: Attention Sustained
- Language
  - WJ-III: Picture Vocabulary
  - PPVT-IV/CPVT
  - Enns Receptive ASL
    - Sign Vocabulary Check
  - WJA: Understanding Directions
- Memory/learning
  - WJ-III Visual-Auditory Learning
- Phonological Awareness
  - TOPEL: Phonological Awareness
  - CTOPP: Sound Matching
- Rapid Naming
  - CTOPP: Rapid Color Naming
  - CTOPP: Rapid Object Naming
- Print Knowledge
  - Letter Say/sign
  - Letter Writing
  - TOPEL: Print Knowledge
  - WJ-III Letter-Word Identification
  - WJ-III Passage Comprehension
  - PIAT-R Reading Comprehension

Questions for direct assessment

1. Does early language skill development (regardless of modality) predict reading skill development in deaf children?
   a) Does one approach (ASL or Oral/Cued/Signed English) produce better outcomes or is language fluency/knowledge the critical factor?
   b) Do different approaches to teaching English have different outcomes?
2. Does early phonological awareness predict reading skill development in deaf children?
3. Does early print knowledge predict reading skill development in deaf children?
4. Does rapid naming predict reading skill development in deaf children?
5. Does attentional capacity affect reading skill development in deaf children?

Questions for surveys

1. Does parental hearing status affect literacy attainment?
2. Does use of residual hearing through amplification/CIs affect literacy attainment?
3. Does pre-implant use of visual language in the home moderate the effectiveness of implantation in promoting literacy?
4. Does the use of any specific communication method in the home contribute to enhanced literacy attainment in school?
    1. Does cross-modal bilingualism (English and ASL) affect literacy outcomes?
    2. Does the use of fingerspelling in the home affect literacy attainment in school?
    3. Does English skill support in the home (via Oral communication or Cued Speech) contribute to enhanced literacy attainment in school?
5. Does increased family support for literacy affect literacy attainment?

Identification Outcomes

- Test assumptions about effective decoding strategies based on “hearing” research.
- Identify the factors critical literacy skill development of in deaf children.
  – Parental, demographic & program factors
  – Communication/language factors
  – Cognitive and experiential precursors to enhanced reading fluency and comprehension.
  – Interactions between communication mode and effective decoding strategies.

Intervention Outcomes

- Guide development of early reading and pre-reading interventions
- These data should allow targeting of pre-reading skills key to this population
  - First language development or attentional regulation vs decoding skill/word reading?
  - Fund of knowledge vs basic reading skills?
  - Writing to read?

Intervention Outcomes

- Potential Focusing of interventions based on the intersection between communication mode and effective strategies
  - Target skills focus based on communication used?
  - Targeting skills based on child characteristics?
- Interventions which target skills leading to reading comprehension, not just decoding.

Tertiary Outcomes

- Potential application to hearing dyslexics and hearing children with visual orientation
- Potential to inform decisions regarding communication approaches for deaf children.
  – Parent-child communication
  – Educational communication

Mryhdlttllmbtsflcwswhtssnw

nyqstns?

Thank you for your attention.

-The VL2 Early Education Longitudinal Study Team

Translation in the Science of Learning Centers

Broad meanings of "translation" across the SLCs

Driven by the needs and demands of the research focus of each center

Examples of Different takes on "translation research" in education

PSLC work on the importance of specification
(which brings to mind David Cohen´s 1999 comment on the policy importance of specification)

LIFE´s work on the importance adaptation to context
(which brings to mind the policy importance of location in a distributed system)

As a group, where are the SLCs with respect to translation?

We seldom speak of transmission (the linear model of hand-off)

We do all speak of "translation" but mean different things by it

Some are speaking of "translation research"

And we have not yet started to talk about transformation

Center´s "translation work" has not been presented as such before, so we have not had a chance to explore our different takes on issues such as

- localization
- grain size of the phenomena under study
- *stages in the translation process*
- agency
- roles

and thus learn from each other methods and approaches

Where could we look for deepening our understanding of research on translation leading to improvement?

One way is to build on the useful framework derived from focusing on improvements in education as a complex system
(Maroulis et al. Science Oct. 1st, 2010)

“mechanism based” (micro-level) “effects based” (macro-level)

“A key challenge facing education research is to integrate insights about “micro-level” processes with evidence about aggregate, “macro-level” outcomes that emerge from those processes.”

Closing Comments

What lies behind considerations of “Fidelity” and “Adaptation”

Fidelity to the *design*

Adaptation to the *environment*

These two stances look at the problem from two different goals

*Scaling up differs fundamentally when what is scaled up is an **intervention** than when it is a **process of change**.*

The focus switches to processes of change because no education intervention is a world into itself – it forces changes in the system that uses it.

On a personal note, going from translation research to implementation research

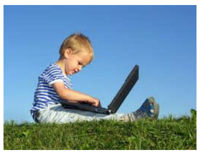
If we look at education as an integrated *complex system* whose outcome is learning,

Where is the missing research, that has just now started to appear?

"Adaptation" to an environment (i.e. learning within organizations)

¨*Sustainability" of improved environments* (i.e. learning ***by*** the educational organization)

And I will end up with an anecdote from LeTUS (learning with educational technologies in urban systems)



E-books and iChats: The role of social interaction in language and literacy

Kathy Hirsh-Pasek, Ph.D.
Temple University, SILC

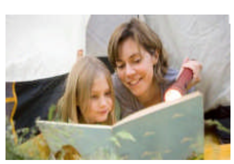
Sarah Roseberry
University of Washington, LIFE

Julia Parish-Morris
Temple University

We are told that children learn best

In ***sensitive and responsive*** environments!

They learn language in conversations

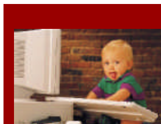


And literacy through "dialogic reading"

That is, young children….

- Are people persons
- Learning in social environments where people respond to their interests and engage them

Yet, increasingly, this social context is giving way to Tech-savvy Toddlers



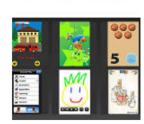
- Children under 3 years spend 3-4 hours per day with screen media

(Christakis, 2009)

- By age 8, children use technology nearly 7.5 hours per day (not including text or phone time)

(Rideout et al., 2010)

- And just this week we learned that there are scores of iphone apps for the toddler set (NYTimes, October 17, 2010) These are advertised as a way to occupy your toddlers.



Can children learn language and literacy when interacting with high tech?

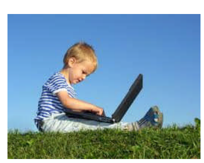
- The evidence is mixed
  - (De Jong & Bus, 2002; Johnston, 1997; Krcmar et al., 2007; Kuhl et al., 2003; Roseberry et al., 2009; Scofield & Williams, 2009; Zimmerman et al., 2007)
- And it depends on the kind of high tech and how it is used.
  - For TV – little language learning before age 2
  - For computer use – some learning

Can technology encourage literacy and language development in ways that mirror live social interactions?

Two recent studies:

1. E-books

1. iChats (or skype)



E-books

Julia Parish-Morris

Kathy Hirsh-Pasek

Roberta M. Golinkoff

E-books (the toddler versions of the Kindle and ipad)

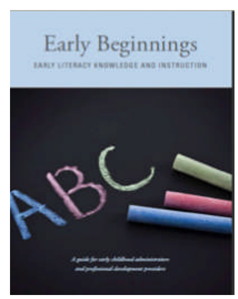
- Electronic console books (e-books) are marketed to children as young as 6 months of age
- 66% of parents agree that educational toys like talking books are "very important" to a child's intellectual development

(Kaiser Family Foundation, 2005)

E-books

- Although many e-books encourage parents to read books with their children, many have headphone jacks so children can operate them independently
  - "When books talk back, every word is an adventure. And with volume control, headphone jack and automatic shut-off, the books don't have to talk too loudly."
    (LeapFrog website—for ages 4-8)

What we know about early reading

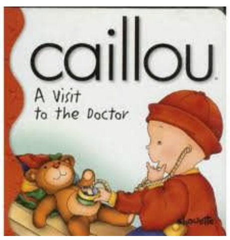


- Parent-child reading experiences are predictive of later literacy
- *Dialogic Reading* is particularly beneficial
  - Contributes to the development of language and literacy skills
    (Chow & McBride-Chang, 2003; Fielding-Barnsley & Purdie, 2003; Hargrave & Senechal, 2000; Heubner & Meltzoff, 2005; Zevenbergen & Whitehurst, 2003)
  - Predicts later school outcomes
    (Hargrave & Senechal, 2000; Karrass & Braungart-Rieker, 2005; Yont, et al., 2003; Zevenbergen & Whitehurst, 2003)

Dialogic Reading

- When adults engage in *dialogic reading* with children, they:
  - ask questions about the story
  - offer expansions, corrections, and praise
  - encourage children's active participation in becoming the teller of the story

(Whitehurst et al., 1988)



- *"Do you remember going to the doctor like Caillou?"*
- *"What do you think Caillou will do at the doctor's office?"*
- *"Can you stick out your tongue like Caillou?"*

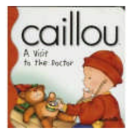
Research Questions

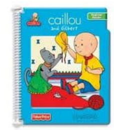
- Do e-books promote the type of dialogic parent-child interactions as traditional books?
- Does children's comprehension of the story differ between e-books and traditional books?

Study Design

- Parents and children (3- and 5-years old) participated in one of 3 reading contexts

E-book | **Traditional Book** | **E-book, no console**

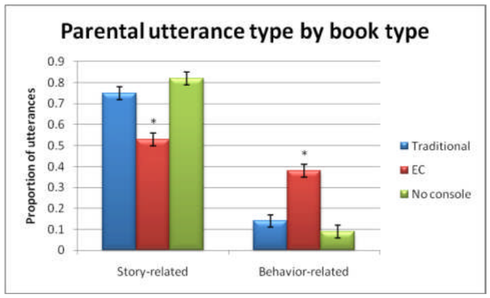




- Reading interactions were transcribed for parent/child language
- Children were tested on story comprehension

- What did we find?

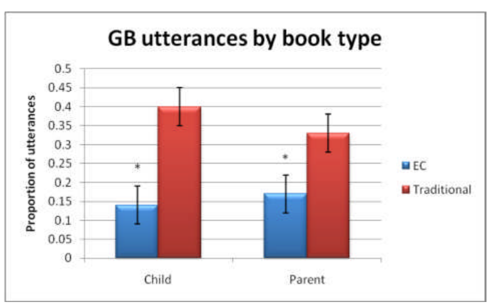
Results – Parental Language



- Parents who read e-books with their children:
  - talked **less** about the story
  - talked **more** about behavior
- The quality of the e-books themselves did not matter (they produced the same language as traditional books!)

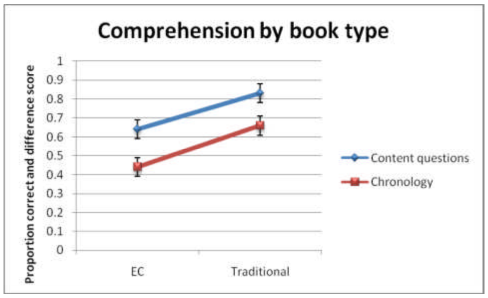
Results – Dialogic Reading

- How often did parent & child utterances "go beyond" the story?



- Parents and children were more likely to engage in dialogic reading with traditional books than with e-books

Results – Child Comprehension



- Children answered more content and chronology questions correctly after reading traditional books
- 3-year-olds required more social support to comprehend the story than 5-year-olds

Conclusions

- Dialogic reading is truncated by e-books
  - Replaced by behavioral directives, which are known to be detrimental to later language

(Barnes et al., 1983; Masur et al., 2005)

- E-books do not foster the type of social interaction that promotes language and literacy

iChats (or Skype)

Sarah Roseberry

Kathy Hirsh-Pasek

Roberta M. Golinkoff

Video vs. Vivo

- Children under 3 years…
  - DO NOT learn language from video
    (Krcmar et al., 2007; Kuhl et al., 2003; Roseberry et al., 2009; Scofield & Williams, 2009; Zimmerman et al., 2007)
  - DO learn language from live social interactions
    (Bloom et al., 1975; Brandone et al., 2007; Childers, & Tomasello, 2002, 2006; Naigles et al., 2005; Tomasello & Farrar, 1986)

But there is a relatively new technology in town…

Introducing Video Chats

- As a video…
  - 2-dimensional screen presentation
- As a live social interaction…
  - Contingent interactions
  - Relevant eye gaze, though not perfectly aligned

What is important about video + social interaction?

- Video chat interactions are contingent
  - Characterized by the synchrony achieved when both partners adjust their communicative timing and content based on the other's responses

(Csibra, 2010; Tamis-LeMonda et al., 2006; Bornstein et al., 2008)

- Contingent interactions facilitate language development – much like dialogic reading

(Chouinard & Clark, 2003; Goldstein et al., 2003; Snow & Ferguson, 1977)

Research Question

- Do young children learn new words from video chats like they do from live social interactions?

Yoked Video ? Video Chat ? Live Interaction

No word learning — Robust word learning

A Difficult Test of Language Learning

- **Verbs** are the building blocks of grammar…

  …yet action words are hard for children to learn

  (Gentner, 1982; Gleitman et al., 2005)

- Using the same test conditions as in the television study of Roseberry et al. (2009), we also asked children to LEARN a verb and to EXTEND the newly label to a new instance of the action.

Study Design

- 24- to 30-month-olds learned new words in one of three ways:
  - Video Chat Training
  - Live Interaction Training
  - Yoked Video Training (a pre-recorded video)

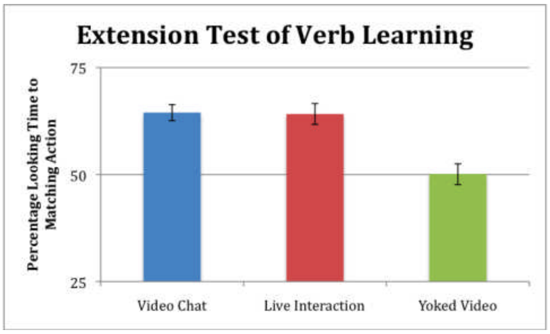
- What did we find?

Results – Quality of Interactions

- How did children respond to video chats compared to live interactions?
  - Children made just as many attempts to interact (i.e., verbally responding to the experimenter, pointing to correct answers, waving) during video chats as in live interactions

- Children participated in video chats, as in live interactions!

Results – Language Learning



- Children who participated in video chats or live social interactions extended their knowledge of the novel verb to a new exemplar
- Children did not learn from pre-recorded video

Results – Language Learning

- Eye-tracking technology revealed that children who looked more at the experimenter's eyes learned the novel words better

- BUT, this only helped when the experimenter's eye gaze was contingent with the child's focus of attention (not the learning session was pre-recorded by the same experimenter who appeared on the television in response to a control child)

Conclusions

- Video chats can be used to generate the type of social interactions that promote language development
- Why? Because social contingency and eye gaze are preserved in video chats allowing it to function as if children are in live social interactions

What have we learned from e-books and iChats?

Social Interaction is Important

- Particularly important for language and literacy are social interactions that:
  - contain the qualities of dialogic reading
    - parents ask questions and offer expansions
    - parents encourage the child to interact

Mechanisms of Social Interactions

- Contingency may be one mechanism of language learning
- BUT children learn language from a medley of cues and we are only beginning to understand this complex process

(Csibra, 2010; Golinkoff & Hirsh-Pasek, 2008; Hollich et al., 2001)

Can technology promote language and literacy?

It depends!

- Technology that fosters social interactions or interactions that approximate social interactions, can benefit children's literacy and language development
  - E-books **do not** accomplish this in their current format
  - iChats **do** create social interactions
- Future technologies like holograms and robots might also enhance children's learning and interaction
  - (e.g. Meltzoff et al. 2009)

Thank you!

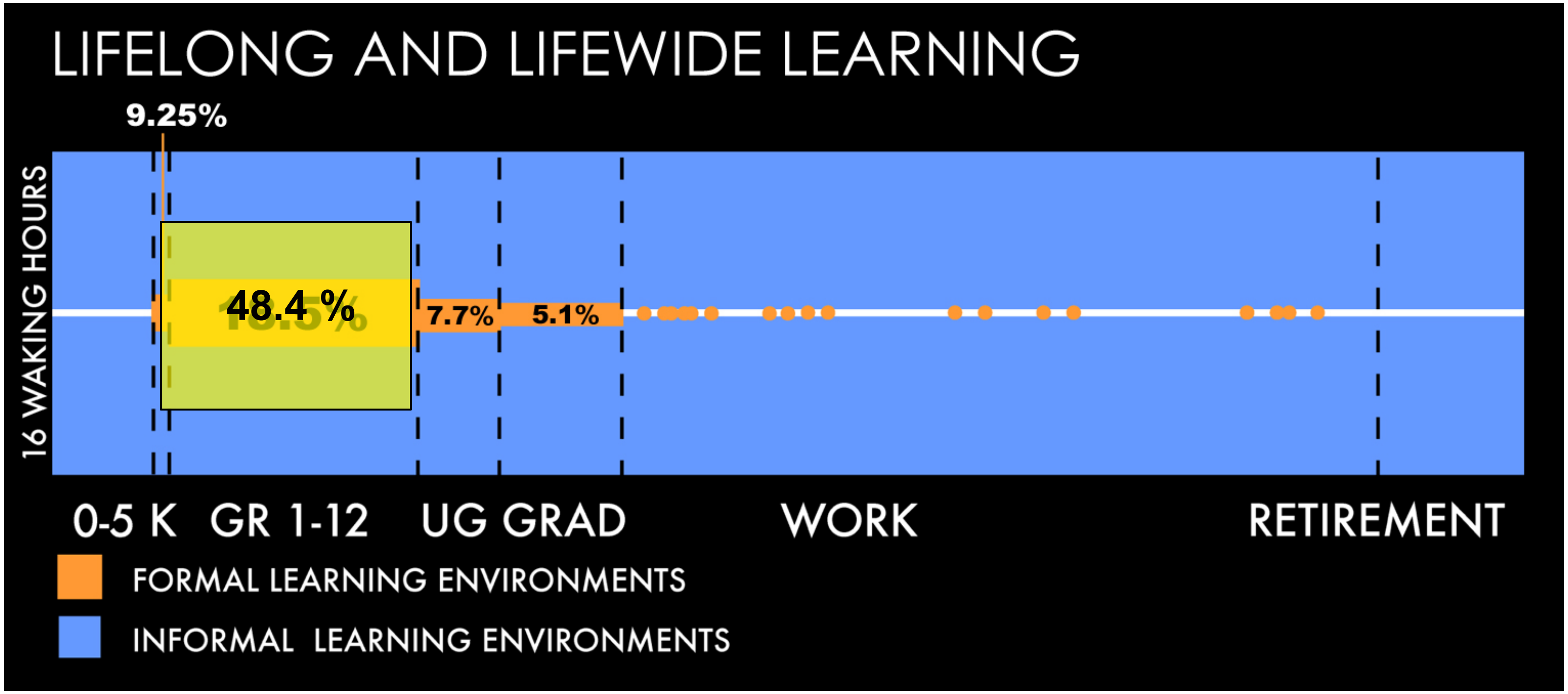
Studying and Fostering Learning through Joint Media Engagement

Reed Stevens
Northwestern University
William R. Penuel
SRI International

Background & Motivation

- Stereotype of media use among children is isolated, passive individuals
- Prior research supports value of *co-viewing:* intentional adult actions to increase learning from television
- *Joint media engagement* expands this focus
- Media effects on learning remains very controversial
- Nearly no *field studies* of learning with media, even television. Dominant traditions of lab and intervention studies.
- Potential for ethnographic studies to inform intervention. Influential in high tech corporate design, why not for technology and intervention design for children?

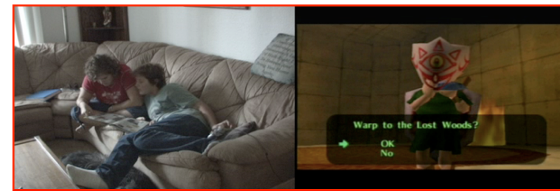
Learning with media is (mostly) in the sea of blue



Line of LIFE Center studies: Learning & Media Controversies

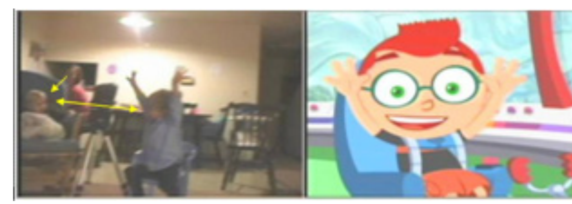
- *Study 1: Video game play (2005-2006)*

  Tweens and teens playing video games at home



- Study 2: *TV viewing (2008-2009)*

  Younger children watching videos and television at home



- Study 3: *Texting & tweeting (soon to start)*

  Teens texting friends and family, tweeting.

The Video Game Playing Field Study

- Studied young people playing games of their own choice in their own homes
- Synchronized In game and in room recordings
- Video based interaction analysis of game play
- These data and analytic techniques allow for analysis of joint media engagement with other people, as well as analysis of in-room learning resources

in room in game

Stevens, R., Satwicz, T., & McCarthy, L. (2008). In game, In room, In world: Reconnecting video game play to the rest of kids' lives. *The Ecology of Games*. Salen, K. (Ed.), Cambridge: MIT Press.

There's plenty of action in the room, not just in the game

- *Learning arrangements*— the social and material arrangements in which game players learn and teach together — are remarkably diverse.

- Source of productive learning during game play is creative ways that young people invented or organized to learn together in-room (learning arrangements), more so than the design features of these commercial games (Gee's argument).

Diversity of learning arrangements in video game play

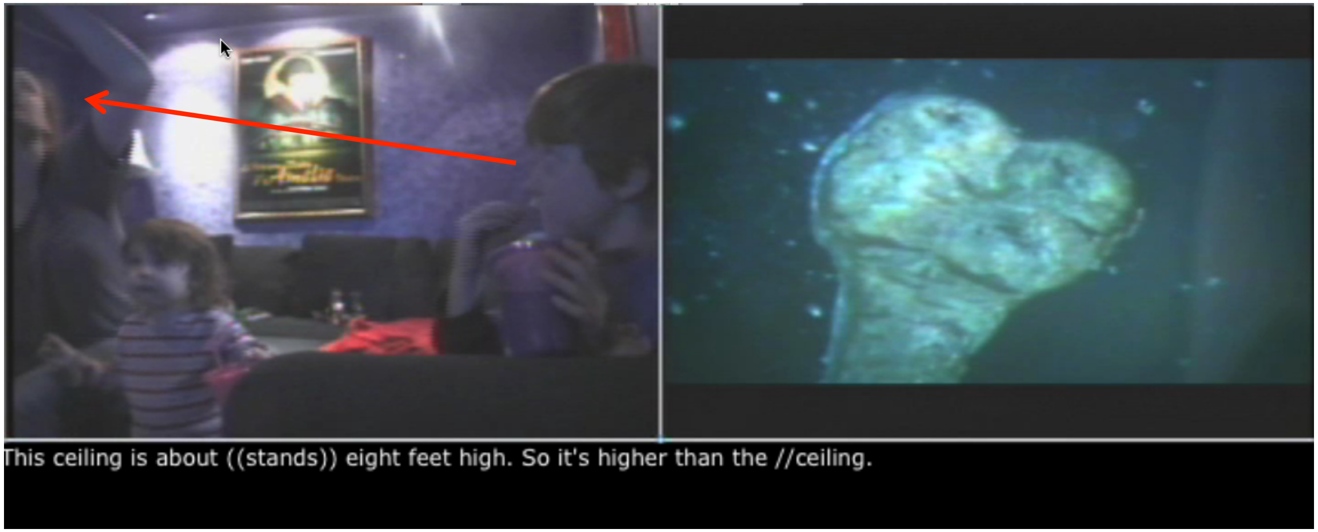
Rachel uses her brother as used as a just-in-time guide and instructor to allow her to pursue customized goals in the game. He is brought in and then sent away.

A physical instantiation of Legitimate Peripheral Participation. Mikey and Ted play in the central space. Little sister Maddy watches from periphery and plays a retired handheld. Sometimes Mikey stops the action and brings Maddy in to give her a chance to try a sub-skill in the game. Then she steps out and game play continues.

Tyler (left) devises multiple ways to demonstrate key moves amidst the flow Andrew's active play, either taking over quickly and displaying his hands as he performs a move or using an inactive controller in Andrew's field of vision

The TV/video viewing study

- Studied young people watching programs or videos of their own choice in their own homes
- Parallel approach to video game study
- Younger children, ages 2 to 6



In room In show

Joint media engagement: enlisting co-participation in the show's agenda

in room   in show

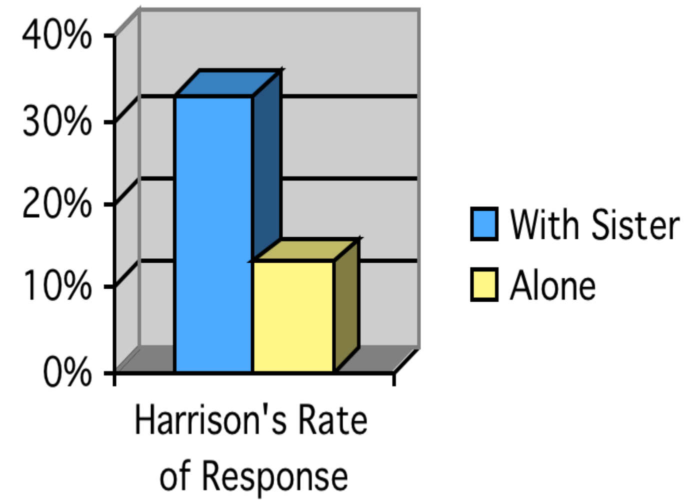
Joint media engagement: collaborative pursuit of a line of emergent inquiry

in room | in show

How and when is "interactive TV" successful at enlisting responses

PROMPT ANALYSIS

- No one responded to more than half of the prompts to which he or she was exposed.
- On average, children responded to 22% of the prompts in a show.
- Overall rates of response ranged from 42% (Preston, age 4) to >1% (Isabel, age 3).
- Great variation between viewing events in the response rates of individual children (e.g., during one session Preston responded to 78% of prompts; on another 17%).
- **Question: why and when do children respond to prompts?**



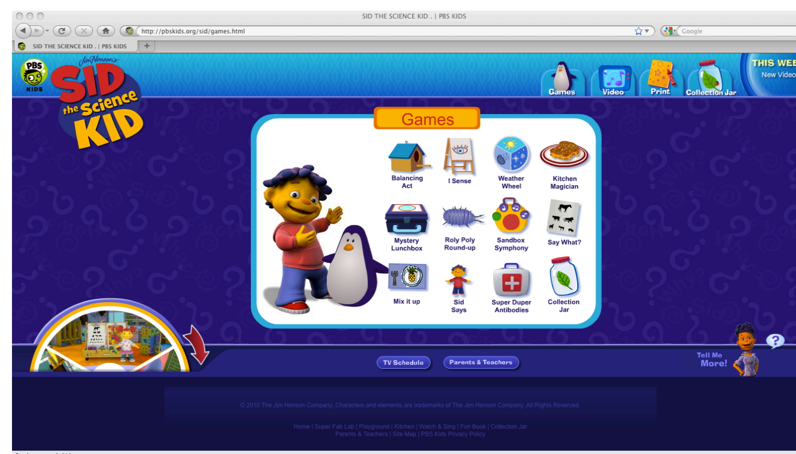
What I hope I've established…

- That in-context field studies promise to tell us new things about how, when, and with whom children learn with media
- That the social aspects of media use and learning, what we call *joint media engagement*, are consequential for that learning
- Studies of this kind are resources for translation into intervention studies…

Fostering Joint Media Engagement

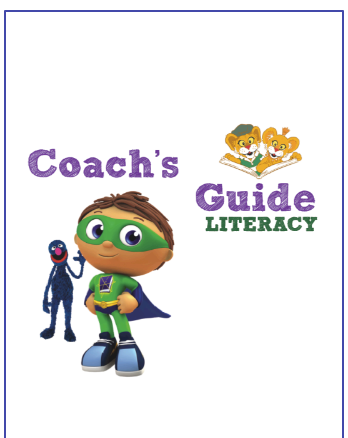
- In the LIFE Center, these ethnographic field studies are informing research aimed at fostering *intent* joint media engagement in early childhood science
  - Relies on content from public media programming from *Sid the Science Kid*
  - Aim is to help children connect learning across different media platforms and settings on specific science topics
  - Working in preschools serving low-income children, helping teachers and volunteer parents adapt and make use of a 10-week intervention

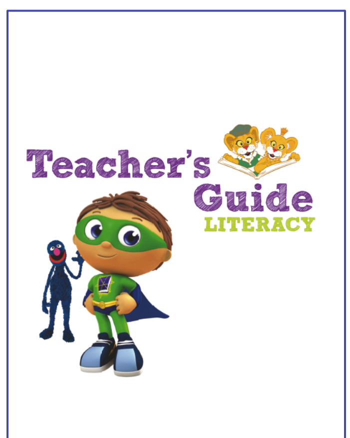
Potential for Broad Impact: *PBS Kids* Media Content Reaches Millions

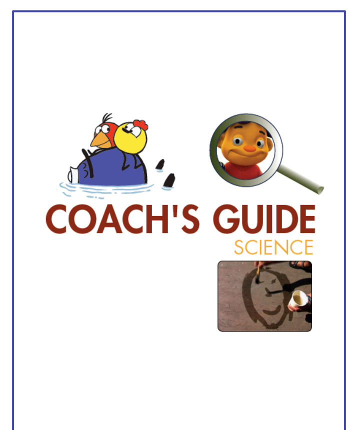


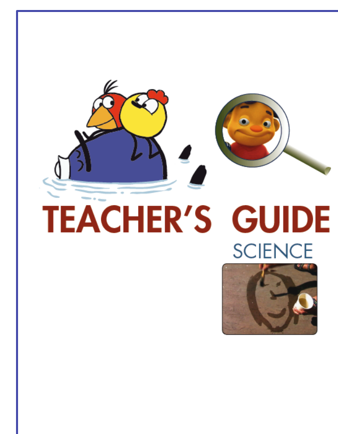
Extending Public Media into Preschool Settings: *Ready to Learn Initiative*

- For the past five years, researchers at EDC and SRI have been examining the impacts of media-rich curriculum supplements on literacy and science outcomes
- Curriculum Supplements Use Media Elements from PBS programs to:
  - Support repeated practice in an engaging context
  - Foster and sustain children's interest in content and skills
  - Provide exposure to context across varied formats ("transmedia"; viewing, playing games, engaging in face-to-face activities)









What Joint Media Engagement Can Look Like

- Clip produced as part of *Ready to Learn* study by Center for Children and Technology at EDC
- Developed for purposes of showing educators and program directors what learning across media formats and joint media engagement in preschool science can look like

Impacts on Children's Science Interest

- In a randomized control trial conducted in 80 preschool classrooms with 398 low-income children, we found:
  - Coaches' guidance in fostering joint media engagement and coordinating activities was successful in promoting high, consistent levels of implementation
  - Children in exposed to the science curriculum supplement expressed more interest in science topics to their female caregivers at home, relative to a control group
  - Although there were no effects of child gender on the results, as some have found, we did find that in the treatment condition, children reported their interest in these topics less often to fathers

Penuel, W. R., Bates, L., Pasnik, S., Townsend, E., Gallagher, L. P., Llorente, C., et al. (2010). The impact of a media-rich science curriculum on low-income preschoolers' science talk at home. In K. Gomez, L. Lyons & J. Radinsky (Eds.), *Learning in the disciplines: Proceedings of the 9th International Conference of the Learning Sciences* (pp. 238-245). Chicago, IL: International Society of the Learning Sciences.

LIFE
Learning in Informal & Formal Environments
LIFE-SLC.ORG

LIFE Study: Fostering Intent Joint Media Engagement

- Work as co-designers with teachers and parents of preschoolers (uncharted territory)
- Jointly develop simple prompts that a range of adults can use to guide joint media engagements
- Use rapid iteration to develop increasingly effective designs that take advantage of learning affordances of digital media artifacts

Early Findings from First Cycle of Design Research

- Early in the implementation
  - Adults paused video to get kids to pay attention, not foster conversation
  - Adults found it easier to mediate children's engagement with computer games
  - Making *selective* use of media was difficult for teachers and parents to do
- Later in the implementation
  - Coach guidance did prompt adults to "transgress" to interrupt viewing with comments
  - Children, on the second and third viewings of clips, became more, not less engaged, after having spent time in direct investigations of phenomena
  - Children picked up language in other settings ("decay," "reversible and irreversible change"

Co-Design Project as a Case of Translational Research

- Ethnographic research findings inform the process by helping the team attend to particular arrangements in settings that can facilitate or hinder joint media engagement to promote learning
- Participation of ethnographic researchers in the design process provides mechanism for feedback and suggestions for design improvements

Collaboration with JGC

ADVISORY BOARD

- **Sue Bredekamp**. Council for Early Childhood Professional Recognition
- **Linda Darling Hammond**, Charles E. Ducommun Professor of Education at Stanford
- **Tom Carroll**, National Commission on Teaching and America's Future
- **Herb Ginsberg,** Herb, Teachers College, Columbia University
- **Rob Lippincott**, Senior Vice President PBS
- **Shirley Malcom**, Head of the Directorate for Education and Human Resources Programs of the American Association for the Advancement of Science (AAAS)American Association for the Advancement of Science
- **Ellen Moir,** Founder, New Teacher Center
- **Sharon Robinson**, President American Association of Colleges of Teacher Educators
- **Susan Zelman**, Corporation for Public Broadcasting
- **Dorothy Strickland**, Samuel DeWitt Proctor Chair in Education at Rutgers University

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Learning in Informal & Formal Environments
LIFE-SLC.ORG

Planned Workshop

- Support from MacArthur Foundation
- Jointly organized by LIFE researchers and the Joan Ganz Cooney Center
- Hosted by Northwestern University
- Objective: Bring leading media researchers to develop a research agenda on joint media engagement for learning

advancing children's learning in a digital age

the Joan Ganz Cooney Center at Sesame Workshop

Informing the Next Generation of Ready to Learn

- Funded projects in the next round of *Ready to Learn* call for innovative interventions aimed at improving low-income children's learning by:
  - Involving the community in design of educational resources
  - Promoting *transmedia* learning: organized resources for learning that support a trajectory of learning across contexts and media
  - Imagines the learner as situated within a community ecology of learning supports

CSCL: From the Lab, to the Classroom, to the “Unowned Spaces” of the Web

Carolyn Penstein Rosé
Language Technologies Institute
and Human-Computer Interaction Institute

LearnLab
Pittsburgh Science of Learning Center

With funding from the National Science Foundation and the Office of Naval Research

Social and Communicative Factors in Learning Thrust

- Co-lead with Lauren Resnick, University of Pittsburgh
- Understanding the role of discussion in learning
- Training teachers to facilitate effective classroom discussions
  - Classroom discourse community, interactional sociolinguistics
  - Accountable Talk (O'Connor, Michaels, & Resnick)
- Eliciting effective interaction between students
  - Computer Supported Collaborative Learning Commuinity, computational linguistics
  - Transactivity (Berkowitz & Gibbs, Teasley, Weinberger, Rosé)

Example of Accountable Talk eliciting productive classroom talk

Eddie: Well, i don't think it matters what order the numbers are in. You still get the same answer. But three times four and four times three seem like they could be talking about different things.

Justification Request

Te[illegible]*u agree or disagree* with what Eddie is saying?

Challenge

Rebecca: Well, I agree that it doesn't matter which number is first, [illegible] they both give you twelve. But I don't get what Eddie means about them saying different things.

Teacher: Eddie, *would you explain what you mean*?

Request Elaboration

Eddie: Well, I just think that like three times four can me[illegible] four things, like three bags of four apples. And four ti[illegible] bags of three apples, and those don't seem like the same thing.

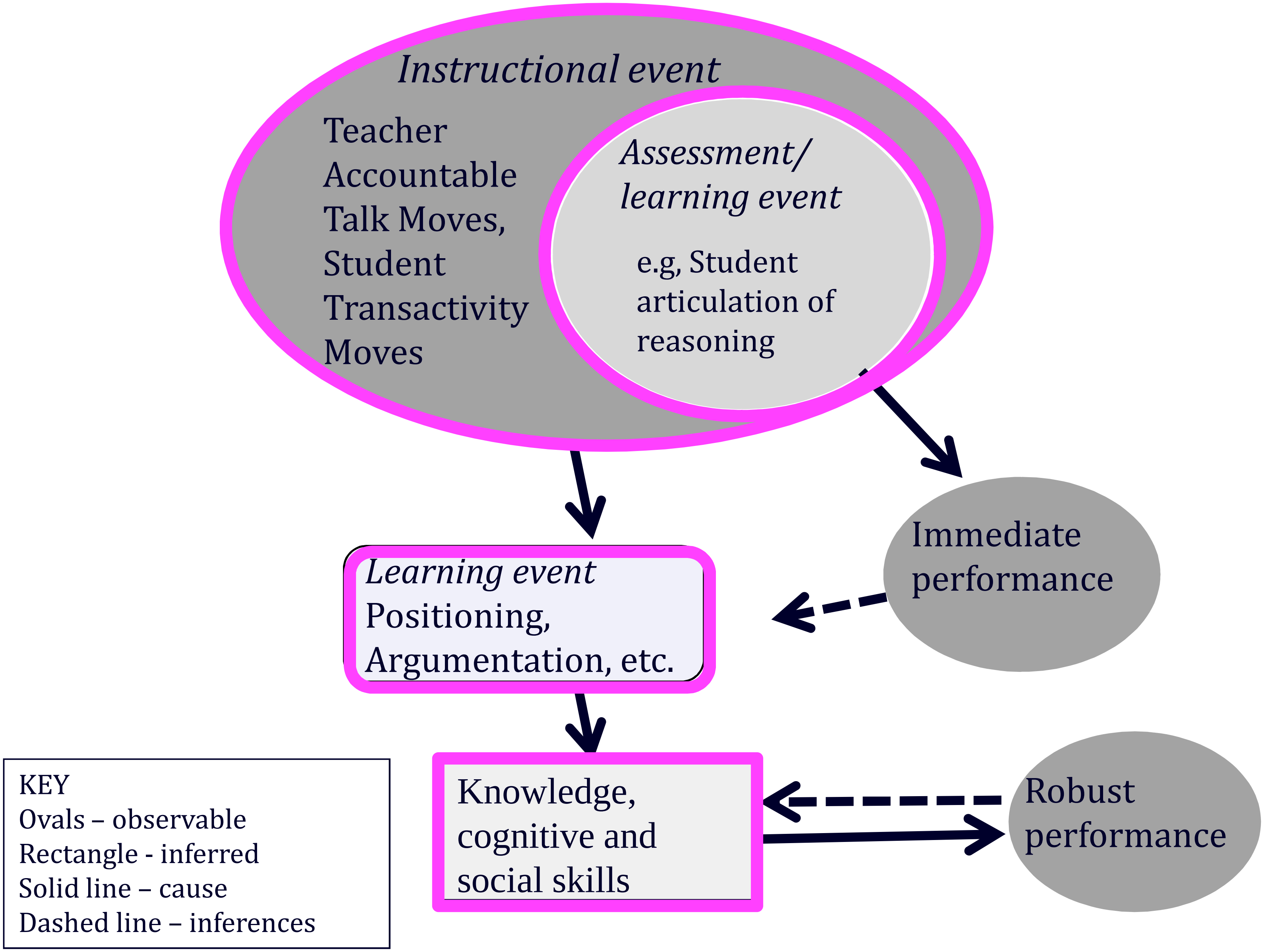
Tiffany: But you still have the same number of apples, so they are [illegible]

Extension

Teacher: OK, so *we have two different ideas* here to talk about. Edd[illegible] order does matter, because the two orders can be used to describe different situations. So Tiffany, *are you saying* that thre[illegible] four times three can't be used to describe two different situations?

Reasoning Critique

Revoicing


Instructional event
Teacher Accountable Talk Moves, Student Transactivity Moves
Assessment/ learning event
e.g, Student articulation of reasoning
Immediate performance
Learning event
Positioning, Argumentation, etc.
Knowledge, cognitive and social skills
Robust performance
KEY
Ovals – observable
Rectangle - inferred
Solid line – cause
Dashed line – inferences

In Vivo Studies

- Combined investigation of Accountable Talk training (for teachers) and CSCL (for students)
- 9th grade biology, district-wide in Pittsburgh Public School district
- Students prepare for whole group classroom discussions in on-line small group discussions

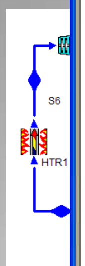
- Questions:
  - How can we use technology to prepare students for whole group interaction?
  - Will effects of interaction support during small group activities transfer into the whole group setting?

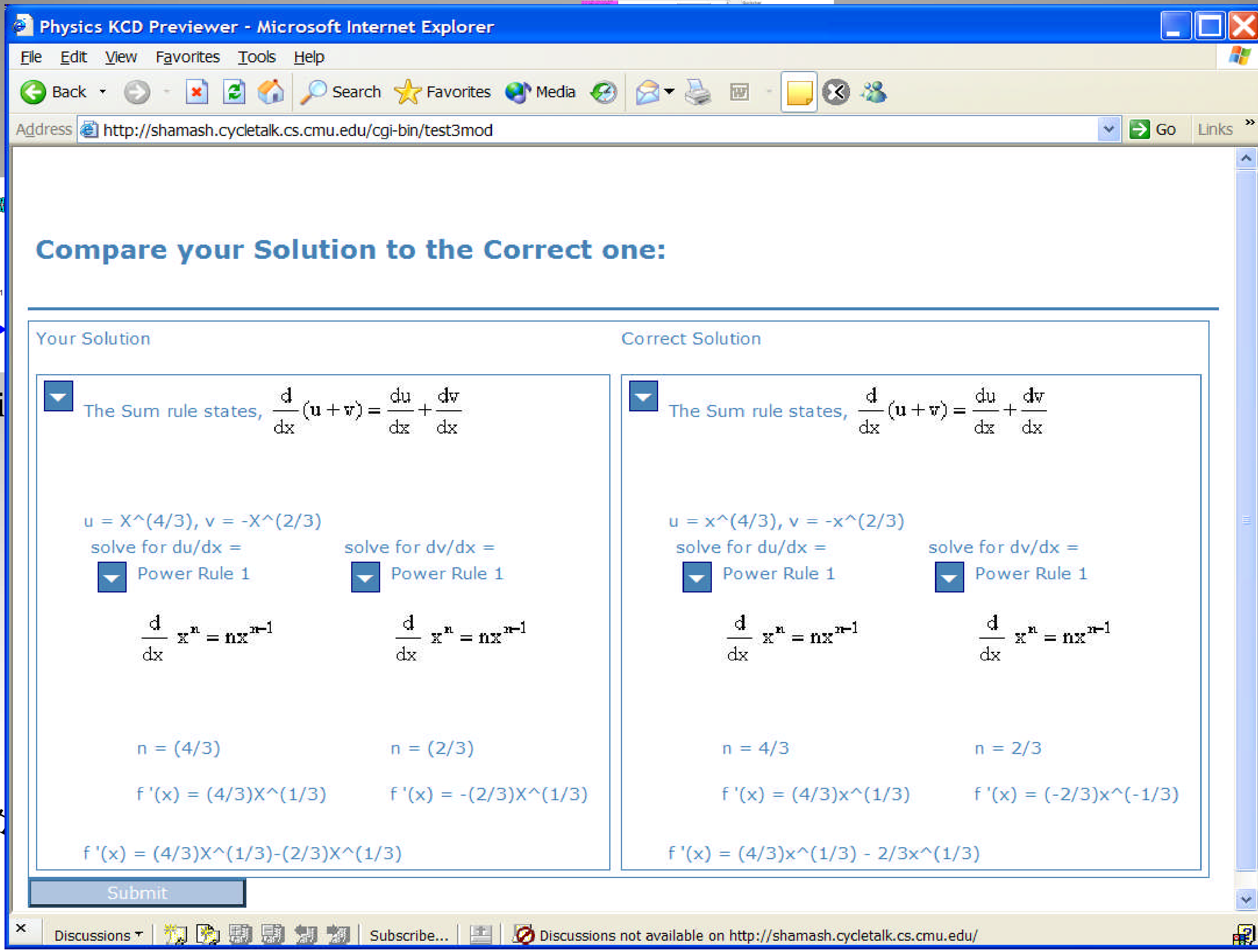

Lab
Classroom
Web
Helping s ents *learn* together in
n-li e gro p ...
Machine Learning
Middle School
High School
Earth Sciences

Ongoing Research Focus

- Identify conversational interactions that are valuable for learning
- Automatic conversation analysis
  - Facilitates learning research
  - Automates assessment of group processes
  - Enables context sensitive triggering of support
- Interactive support technologies

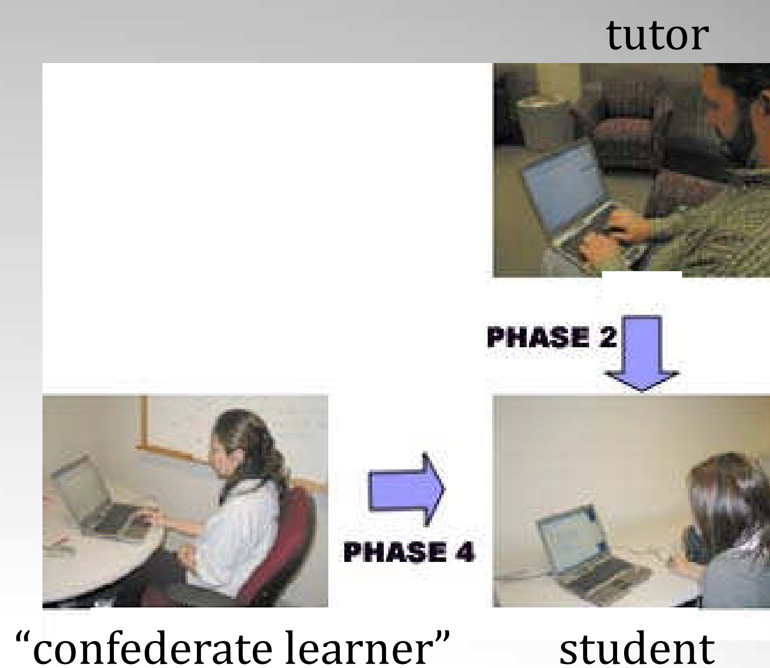
Starting with lab studies…





Investigating Support Needs with Different Types of Partners

- Different needs with different types of learning partners
- Experimental Design
  - Use confederates as learning partners
  - Ability level :
    High (HI) vs. Low (LO)
- Problems Identified
  - Shallow explanations
  - Paucity of teaching behaviors within teams



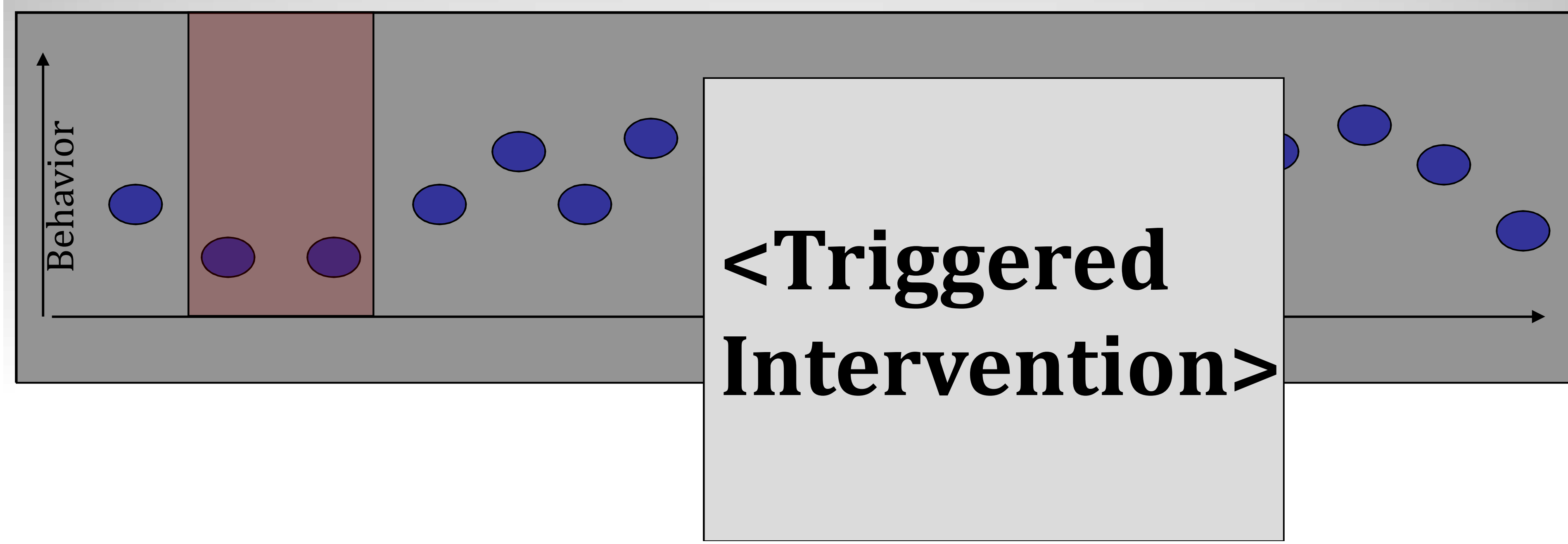
Investigating the Potential Impact of Dynamic Support

- Experimental Design
  - Ability level : High vs. Low
  - Dynamic Support: Prompt vs. No Prompt
- Prompts elicited additional attempts at explanation
- Significant benefit for prompting on student learning ($F(1,37) = 4.12$, $p < .05$, effect size .66)

Case	Prompts
1	The other student would benefit from more explanation. Please elaborate on your correction.
2	Help the student understand your correction. The other student seems to be struggling with this section of the problem. Please offer your assistance.
3	Please be sure you are working with the other student to solve the problem. It seems like the other student has not contributed lately. Why don't you see if they need help?
4	It seems like you are moving on before understanding your errors. Please spend more time reviewing this page. Does the other student understand the errors made on this problem? Please share your understanding of this page with the other student.

Monitoring Collaboration with Machine Learning Technology

Download tools at:
http://www.cs.cmu.edu/~cprose/TagHelper.html
http://www.cs.cmu.edu/~cprose/SIDE.html



Modeling Visual Navigation Using Optic Flow

Florian Raudies

SLC 2010, Washington DC
10/15/2010

A National Science Foundation Science of Learning Center

CELEST
Center of Excellence for Learning in Education, Science, and Technology

BOSTON UNIVERSITY

Department of Cognitive and Neural Systems

Overview

Collaborations & Projects

Within CELEST

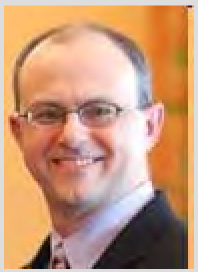
Segmentation of Flow for Visual Navigation

From Bench to Applications through Modeling

Conclusions

Collaborators & Projects

Development of the Visual Motion System



Rick Gilmore
Pennsylvania, US
Developmental Psychology

Visual Perception & Learning

Motion Transparency & Binocular Transparency

Heiko Neumann
Ulm, Germany
Vision and Perception

Figure Ground Segregation

Pieter Roelfsema
Amsterdam, Netherlands
Vision and Cognition

Modeling Visual Navigation

Micheal Hasselmo
Boston, US
Dynamics of Memory-guided Behavior

Ennio Mingolla
Boston, US
Modeling with Neural Networks

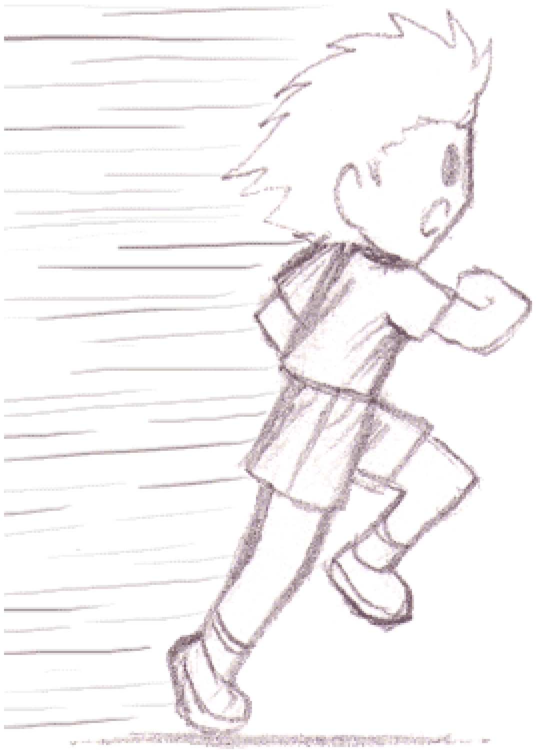
Within CELEST

Exploring mechanisms of visual navigation by modeling of

visual motion processing

estimation of ego-motion

segregation of independently moving objects



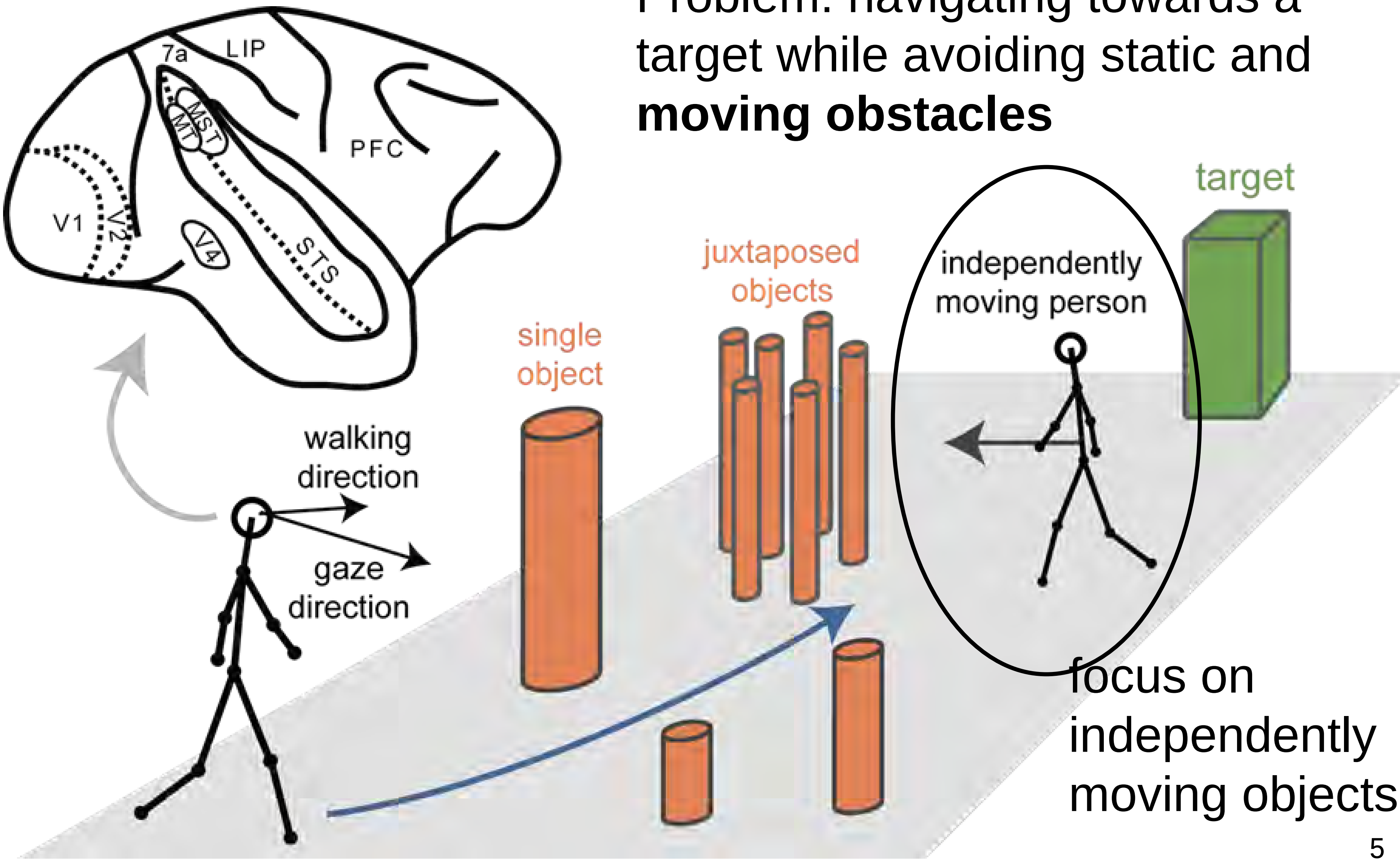
Working on **functional connections** and **neural plasticity** by designing neural network models with plasticity which

reflect sensitivity to visual motion of infants & adults

simulate shift of gaze

Visual Navigation

Problem: navigating towards a target while avoiding static and **moving obstacles**

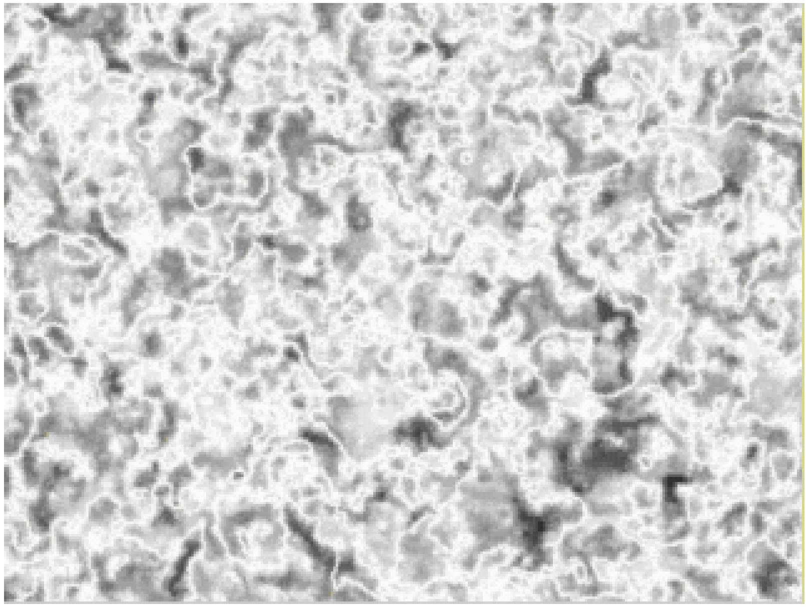


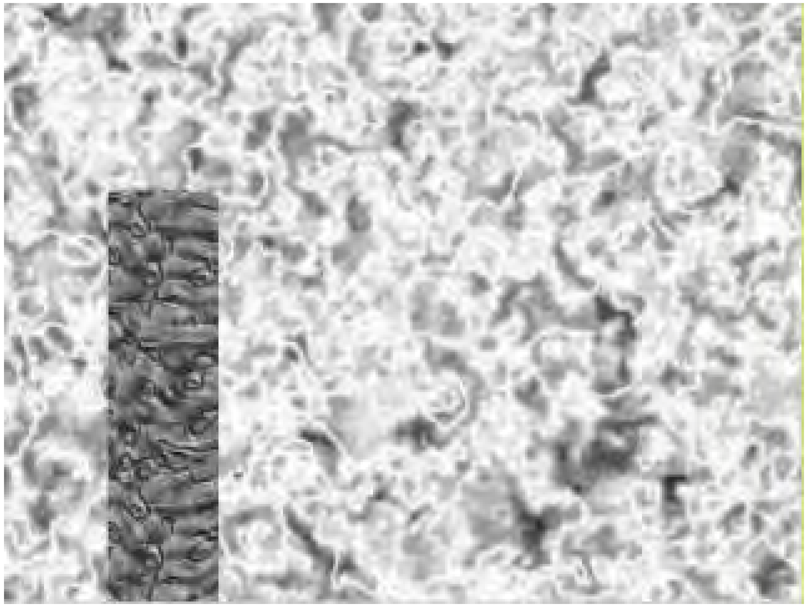
focus on independently moving objects

Segmentation of Flow for Visual Navigation

Problem: independently moving objects influences the estimated ego-motion

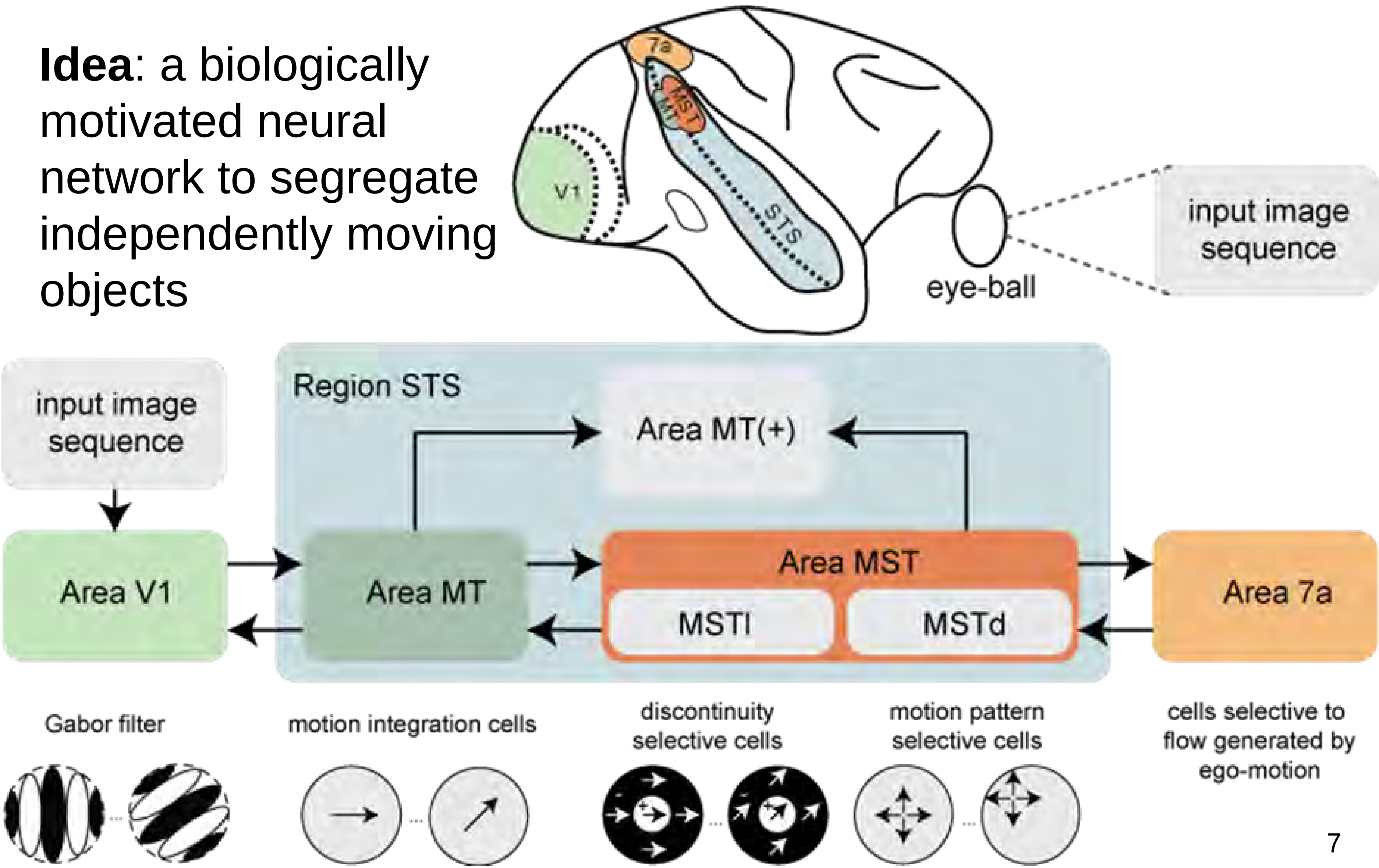
Heading towards a wall in the back





Segmentation of Flow for Visual Navigation

Idea: a biologically motivated neural network to segregate independently moving objects



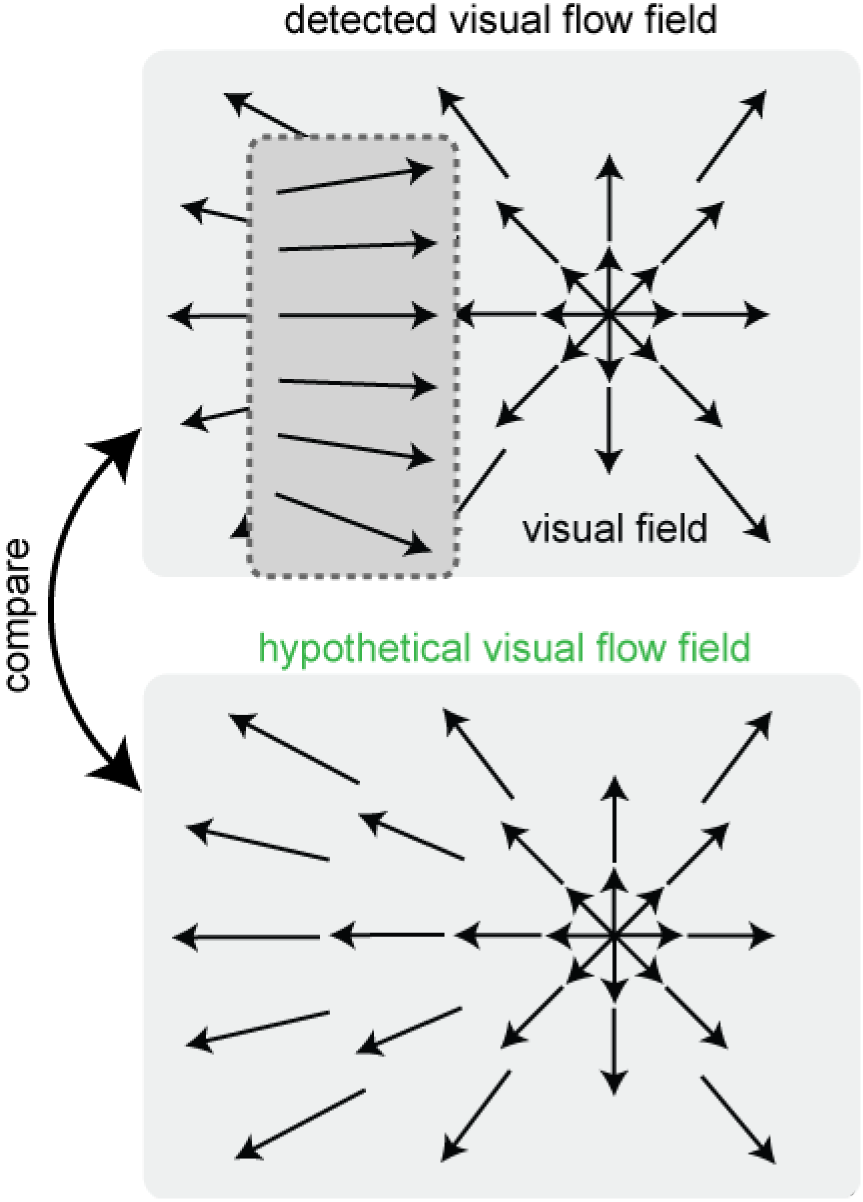
Segmentation of Flow for Visual Navigation

Function of the network

Construct **hypothetical flow** based on estimated ego-motion

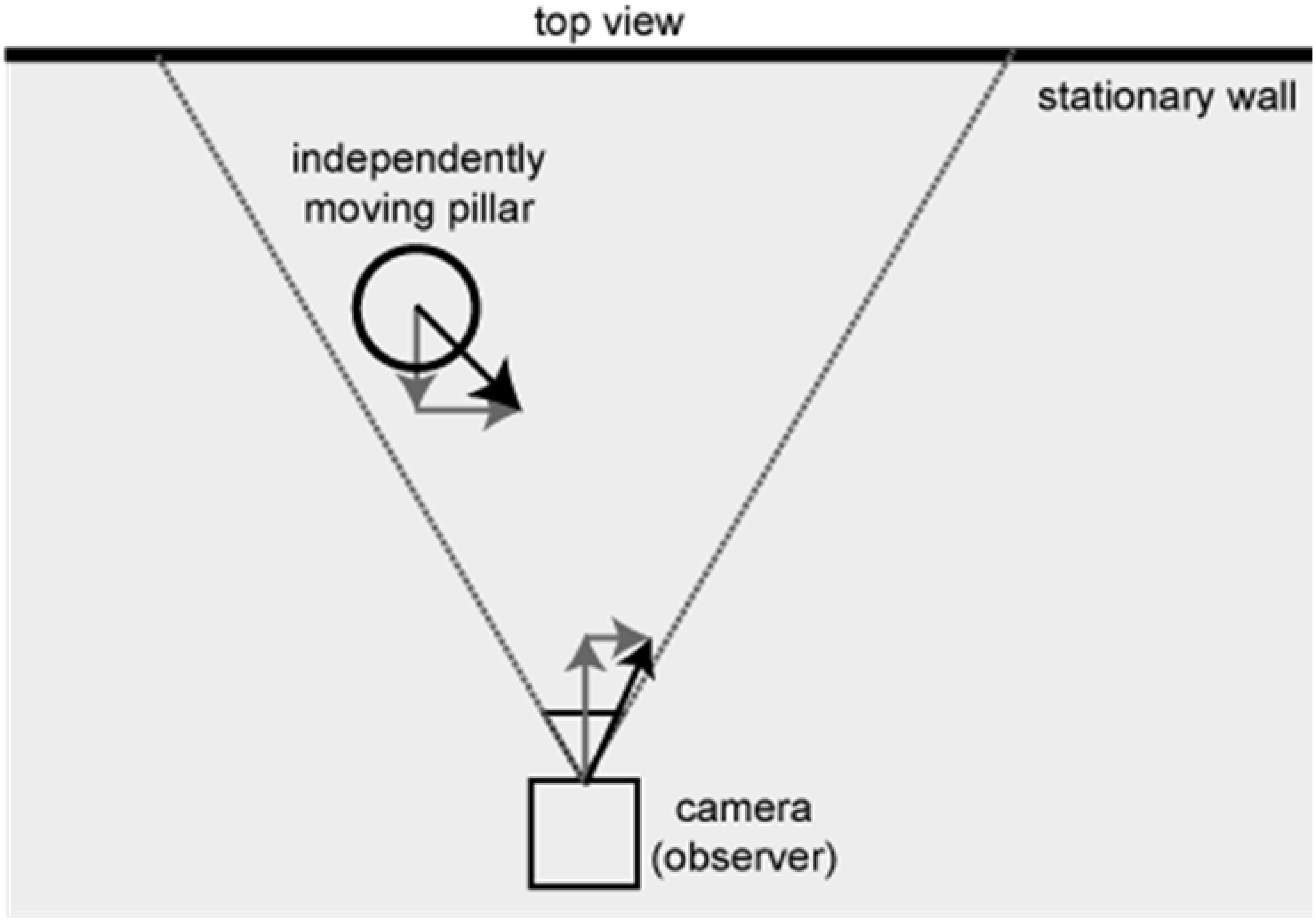
Compare hypothetical and detected visual flow

Spatial locations of **disagreement** are those of independently moving objects



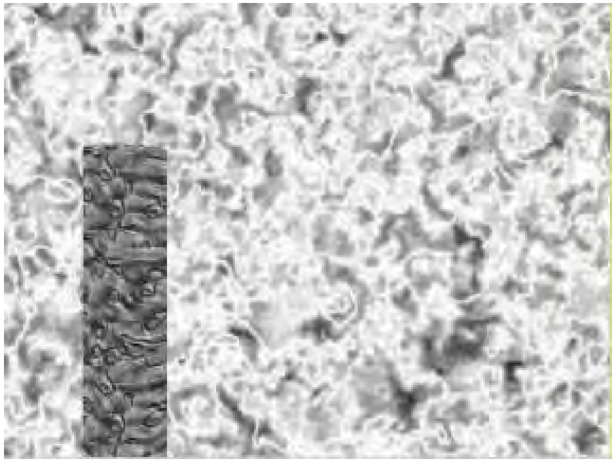
Segmentation of Flow for Visual Navigation

Scenario: independently moving pillar

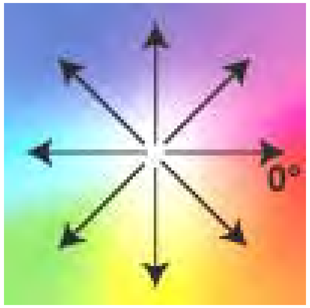


Segmentation of Flow for Visual Navigation

Simulation results for ego-motion towards wall

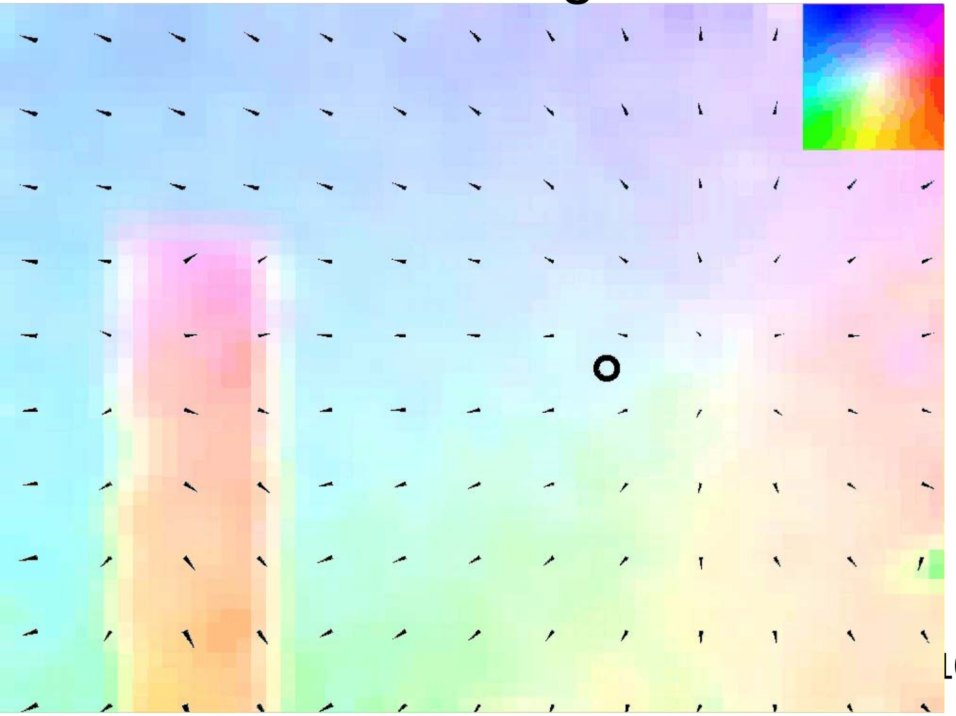


Color code



Flow based segmentation

Flow & estimated ego-motion

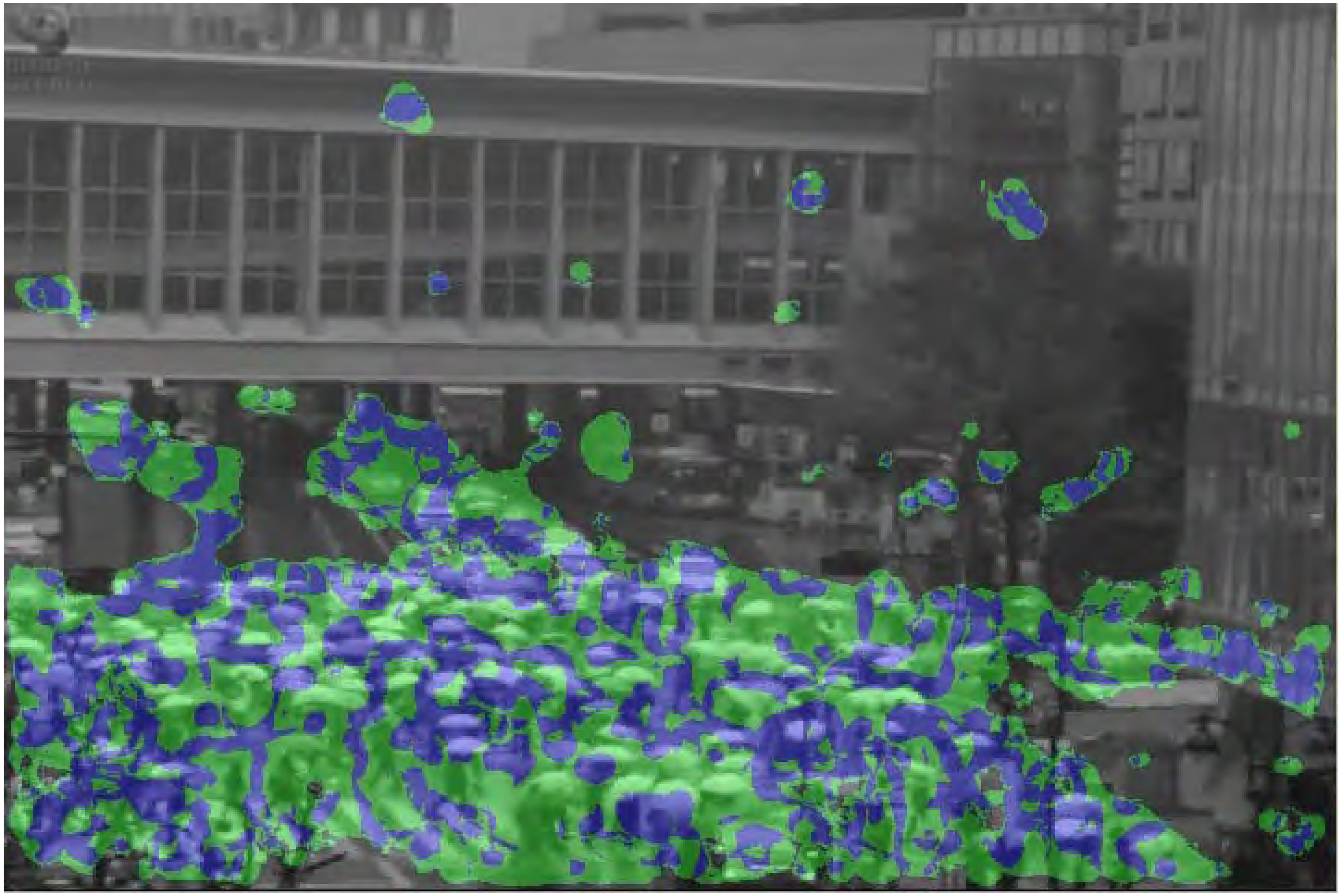


From Bench to Application through Modeling

Goal: detection of semi-transparent regions for surveillance to zoom to these regions

From Bench to Application through Modeling

Segmentation result for
semi-transparent (blue) and opaque motion (green)



Summary & Conclusion

CELEST provides a platform to explore methods of navigation

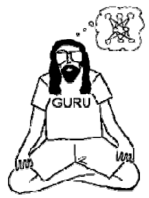
Here I presented techniques for the detection of image flow, estimation of ego-motion, and segmentation of moving objects

Topics of development, learning, and self-organization of the visual system are being addressed in collaboration with Rick Gilmore

Interaction with Students

Guest lectures for the course
“Adaptive Robotics”

Thank you!



A model of early sensory processing in audition and vision

Dr. Honghao Shan!
As told to (and by) Gary Cottrell
gary@ucsd.edu

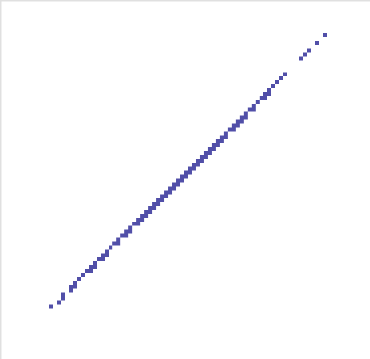
A tad of background

- Why are sensory cells the way they are? (center-surround ganglion cells in retina, edge-detectors in V1, etc.)?
- One set of ideas are the *efficient coding, sparse coding* or *redundancy reduction hypotheses* (Attneave, Barlow, Field, Olshausen):
  - The goal of the visual system is to learn the statistical structure of its environment by reducing the redundancy in it
  - By doing this well, it can represent the world efficiently.

A simple (unrealistic) example

- Suppose two input signals (e.g., pixels) are completely correlated:

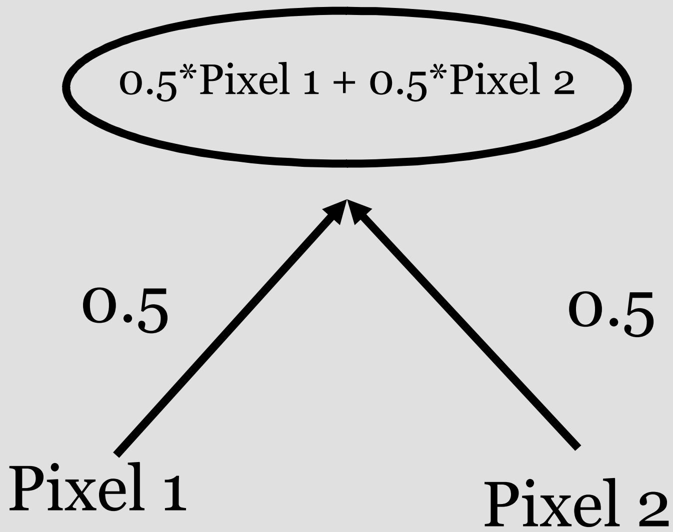
Pixel 2



Pixel 1

A simple (unrealistic) example

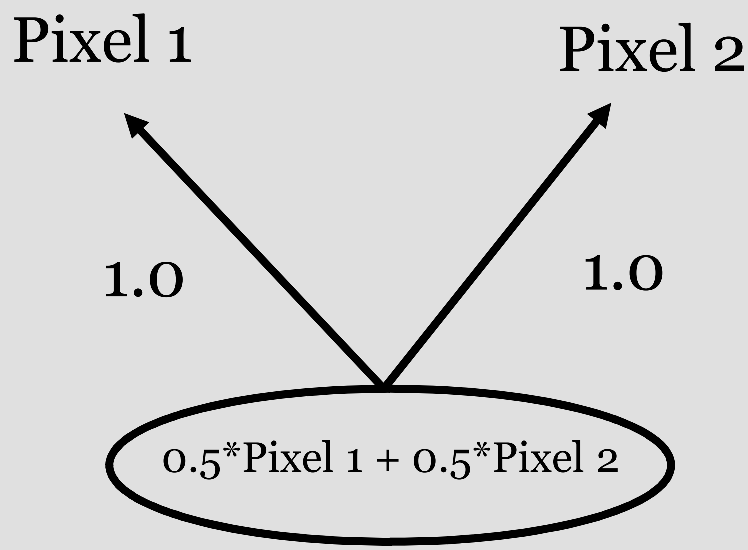
- Then we could represent that information with one (linear) neuron:



- This is an example of redundancy reduction

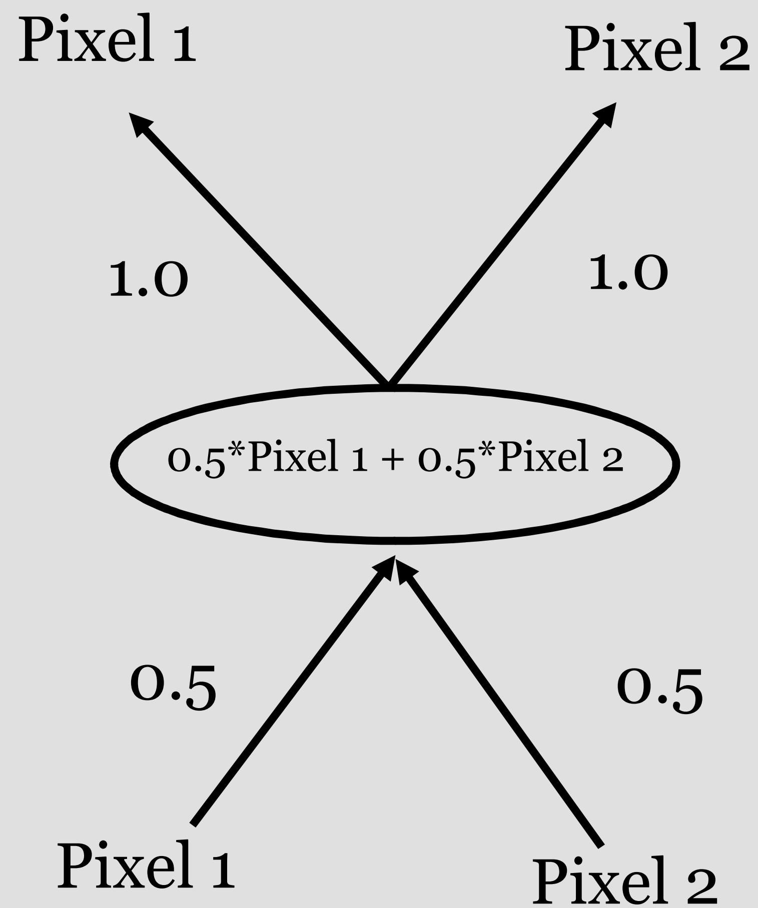
A simple (unrealistic) example

- Furthermore, we can *reconstruct* the original pixels from that one "neural response":



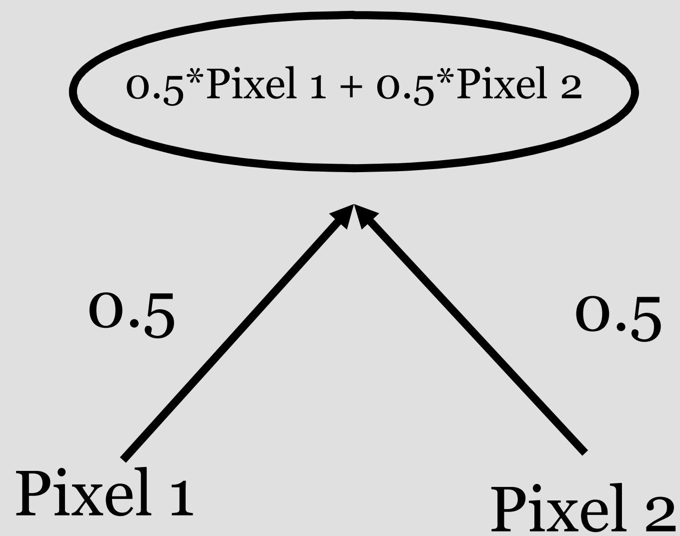
A simple (unrealistic) example

- Hence the "autoencoder network":



Principal Components Analysis

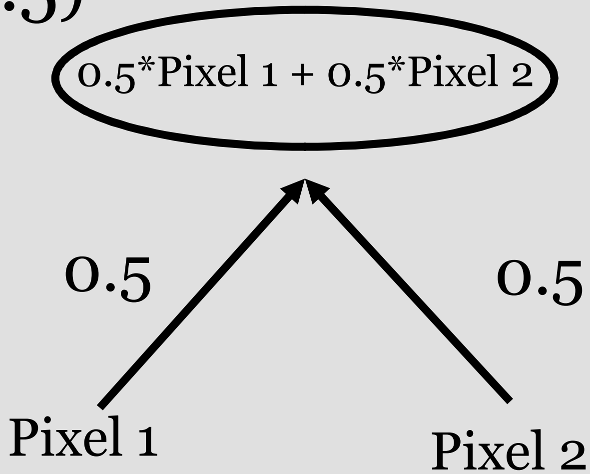
- Principal Components Analysis would do exactly this, because it learns representations based on correlations between the inputs.

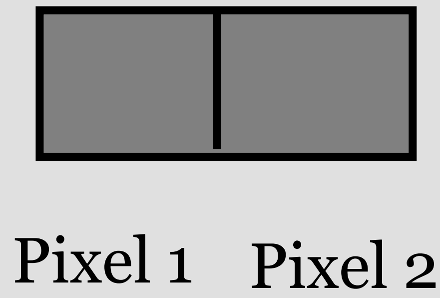


- This is an example of redundancy reduction **and** dimensionality reduction (from 2 dimensions to 1)

Principal Components Analysis

- Note that we can plot this “principal component” in image space, corresponding to the “weights”, (0.5,0.5)

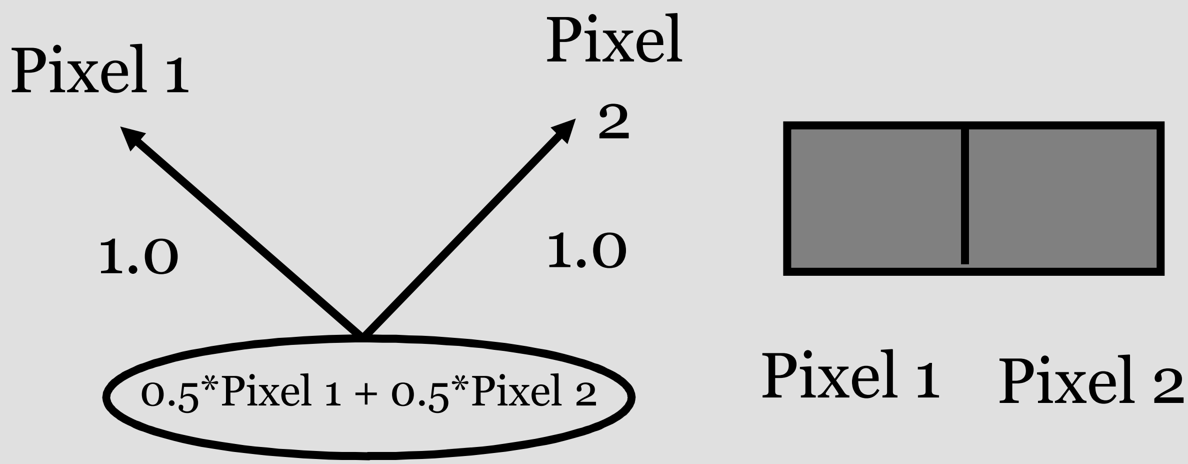




- The same thing applies if we have more than two pixels…so we have more than 2 principal components…capturing more correlations…

Principal Components Analysis

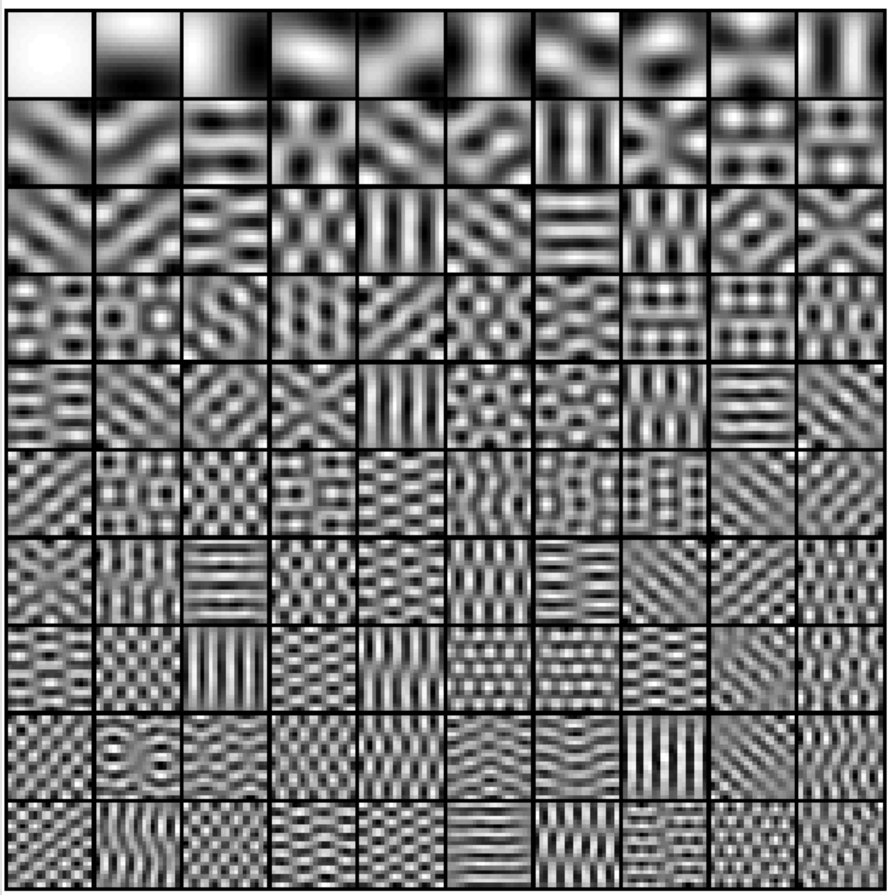
- And now we can see that the reconstruction is a weighted version of that "image"



- The same thing applies if we have more than two pixels…so we have more than 2 principal components…capturing more correlations…

Principal Components Analysis

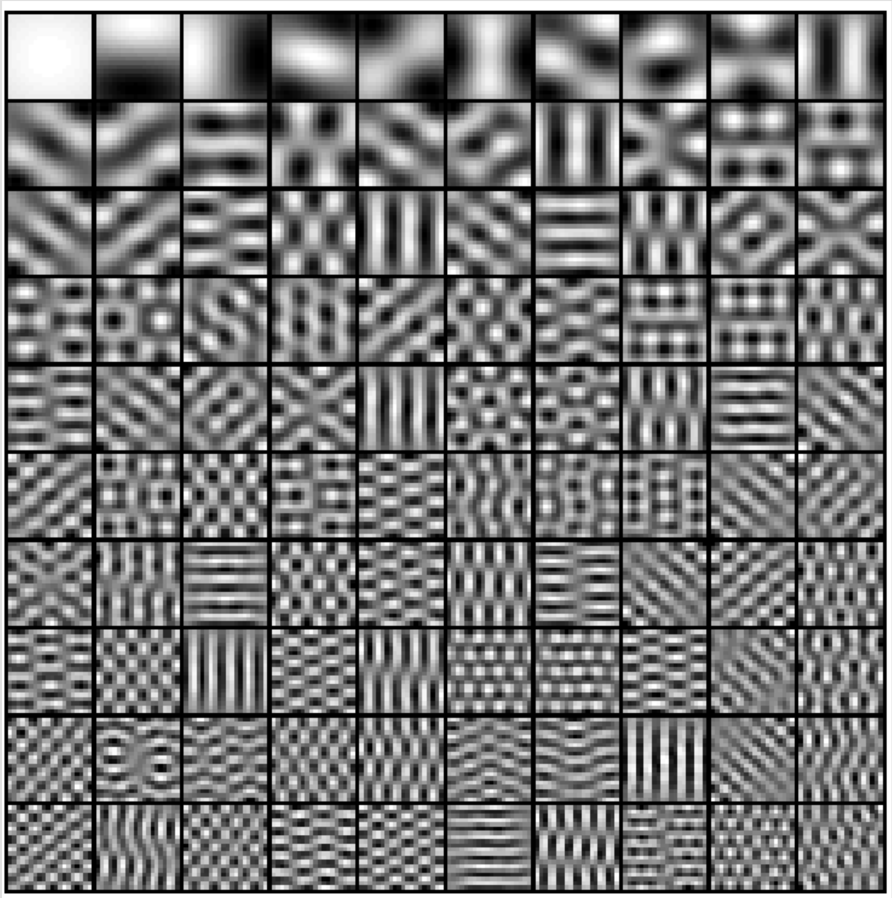
- Here are the principal components of 10x10 patches of natural images:



Principal Components Analysis

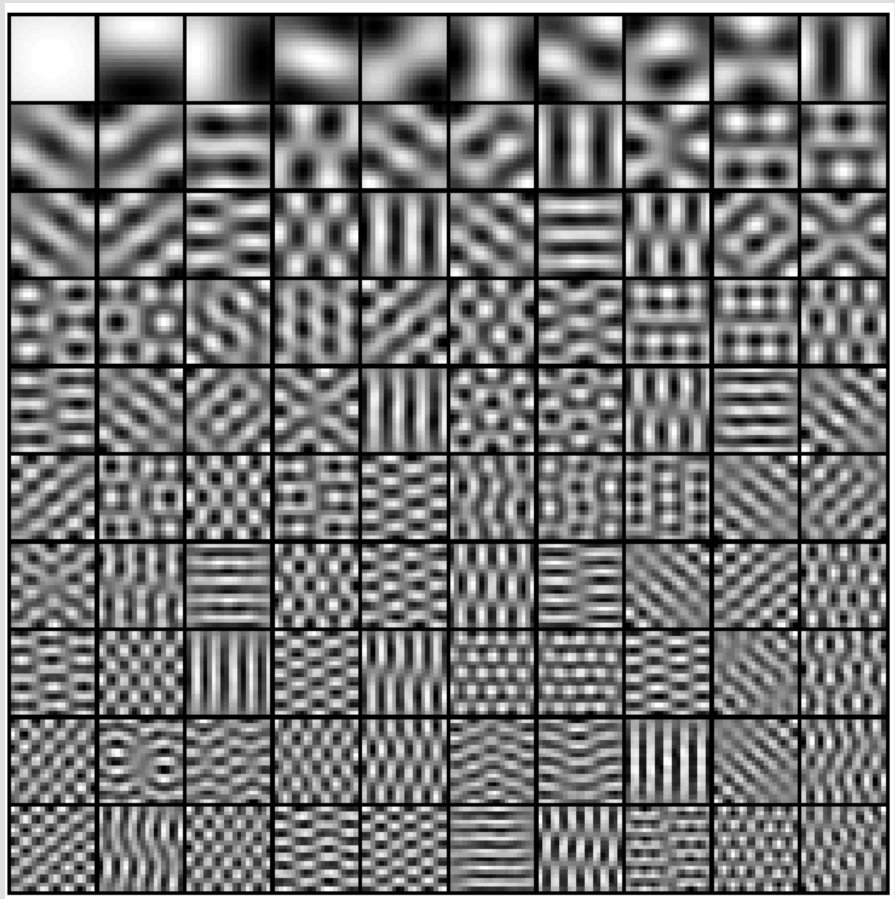
- But PCA learns these correlations in order of their size: so the first principal component does a ***lot*** of work:

1st PC



Principal Components Analysis

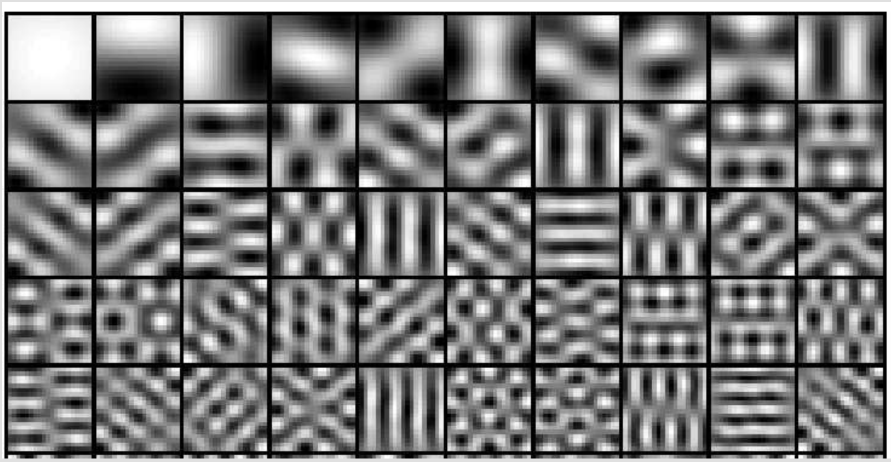
- and the last principal component does ***very little*** work:



last PC

Principal Components Analysis

- So we can throw a lot of them away and you can't tell the difference in an image that was reconstructed from them:



Principal Components Analysis

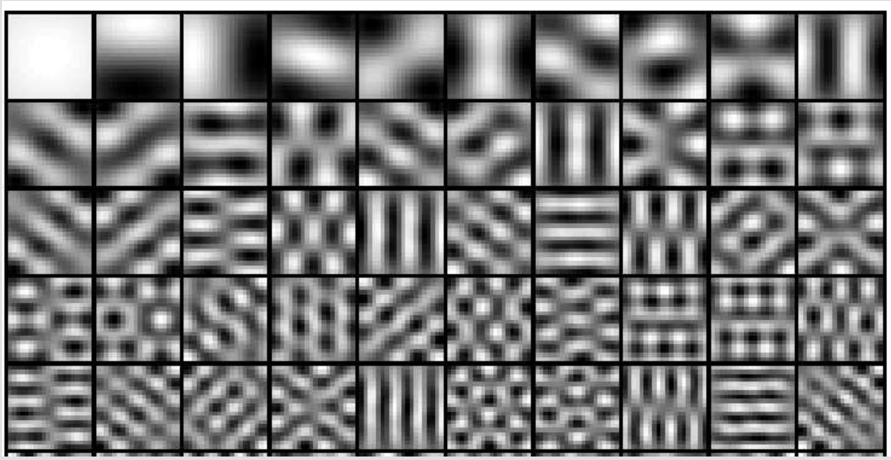
- So PCA does two things right: It *decorrelates* the inputs, and it reduces dimensionality, making it "efficient" at encoding images…

Original

Compressed

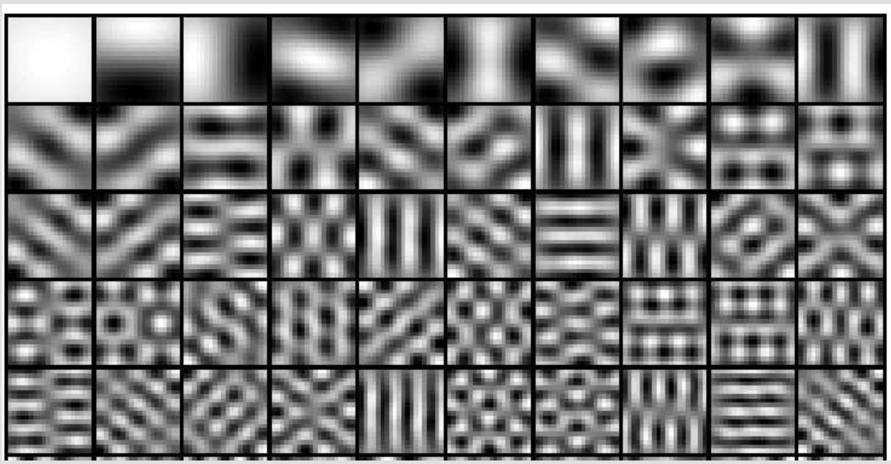
Principal Components Analysis

- But no neuron should have to be the first principal component: So we should distribute the load evenly - this is called "response equalization."



Principal Components Analysis

- Secondly, PCA is profligate with connections - every pixel is connected to every principal component "neuron": we should try to reduce the connections also.



Sparse Principal Components Analysis

- We will try to minimize reconstruction error,
- While trying to equalize the neural responses
- And minimizing the connections.

Sparse Principal Components Analysis

- We minimize:

$$E = \left\langle \frac{\|\mathbf{x} - \mathbf{A}\mathbf{s}\|_2^2}{2} \right\rangle + \lambda \|\mathbf{A}\|_1$$

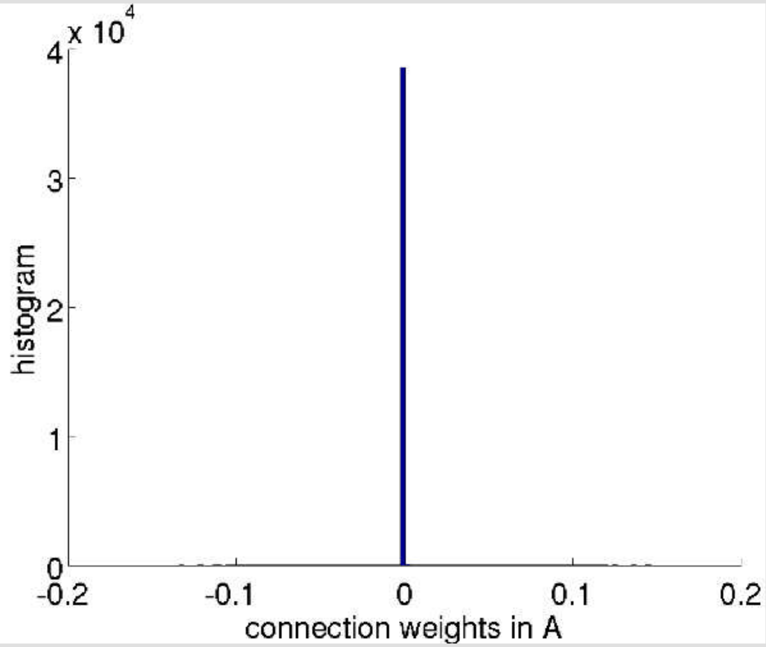
- Subject to the following constraint:

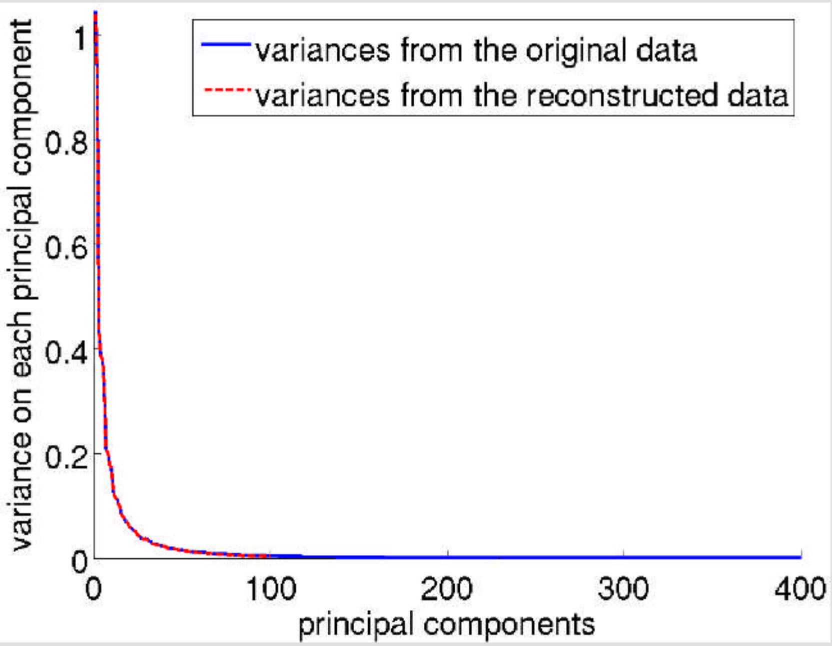
$$\langle s_i^2 \rangle \leq 1 \quad \text{for } i = 1, 2, \ldots, M$$

Information Kept With Sparse Connections

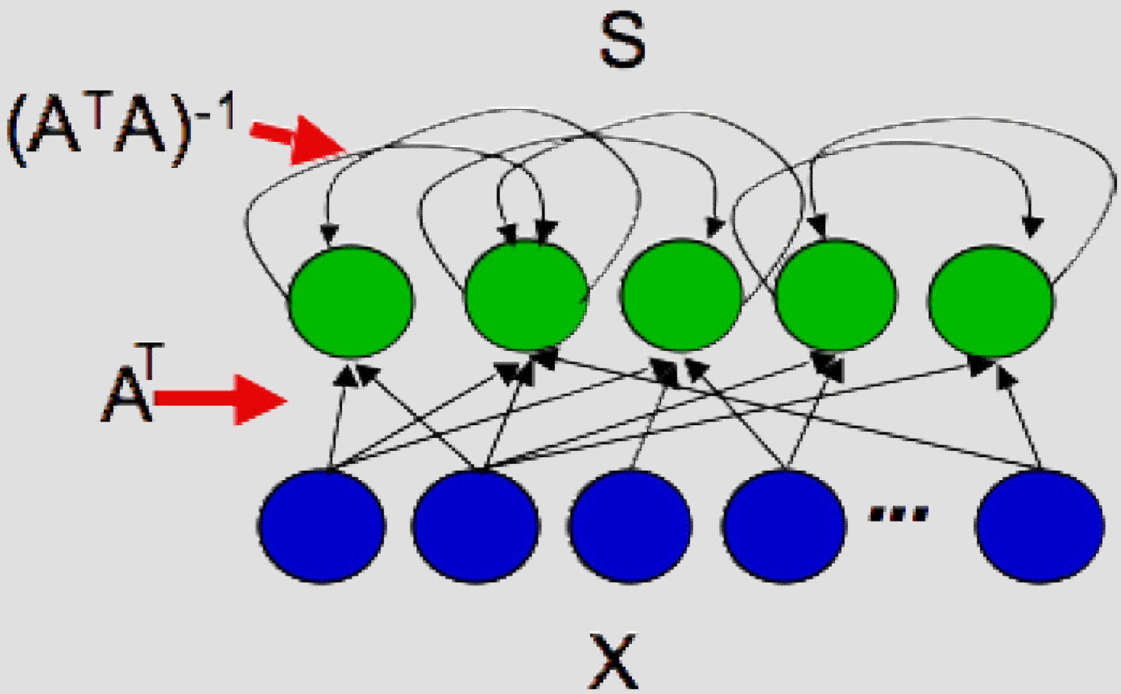
- the model is applied to 20 X 20 image patches, and the dimensionality reduced to 100.
- Our model captures 99.23% of the variance that *could* be captured by an optimal linear model with 100 output neurons.
- ***96.31%*** of the connection weights in our model are ***zero***.

Information Kept With Sparse Connections





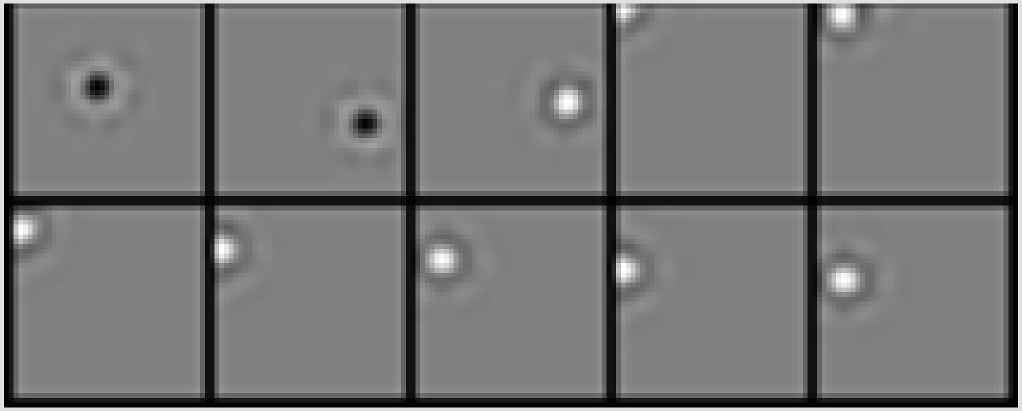
The model as a neural net…



It is A^T that is mostly 0…

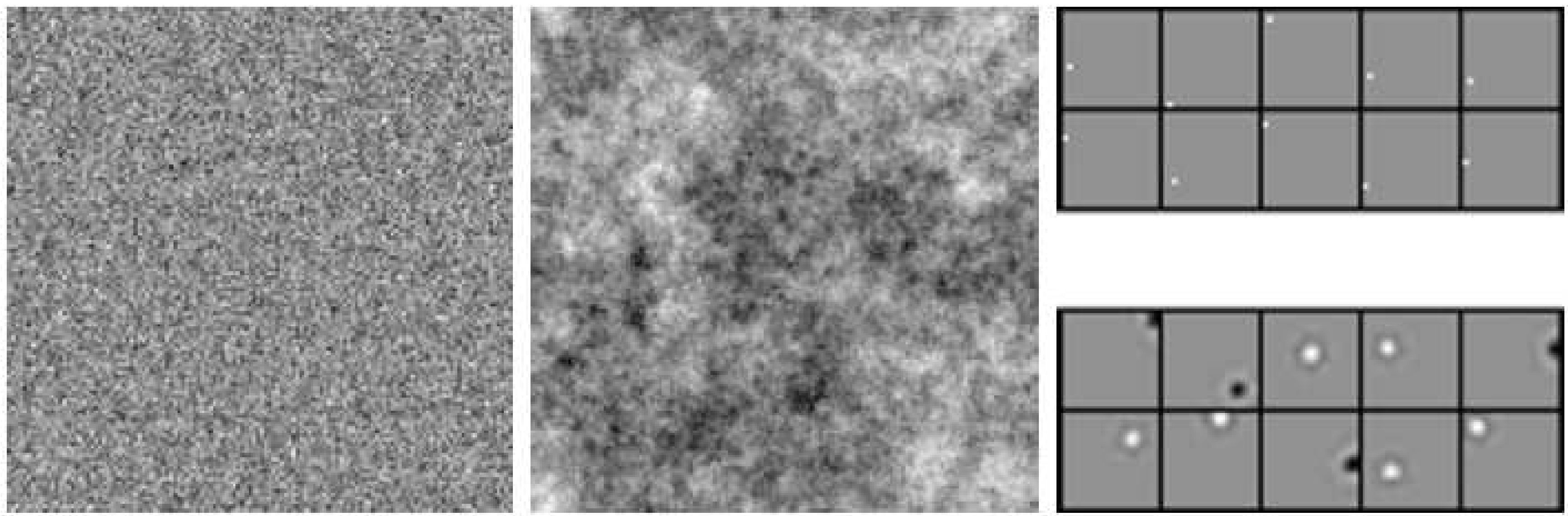
Results

- On grayscale images:



- Note that we get essentially the *same* results applying the model to pink noise images…

Results

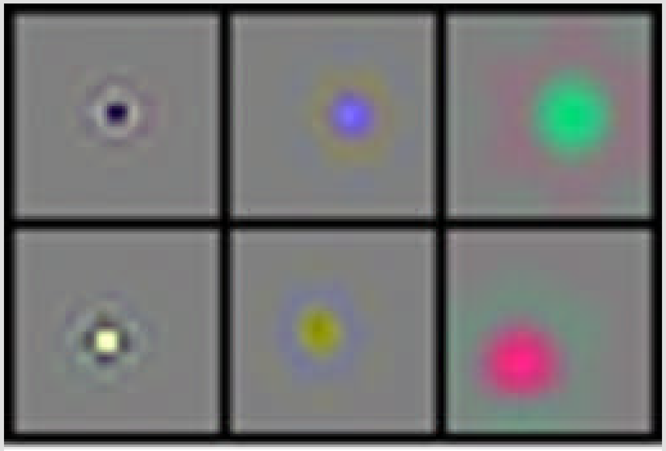


(e) White noise (f) Pink noise (g) Learned filters

- suggesting the 1/f power spectrum of images is where this is coming from…

Results

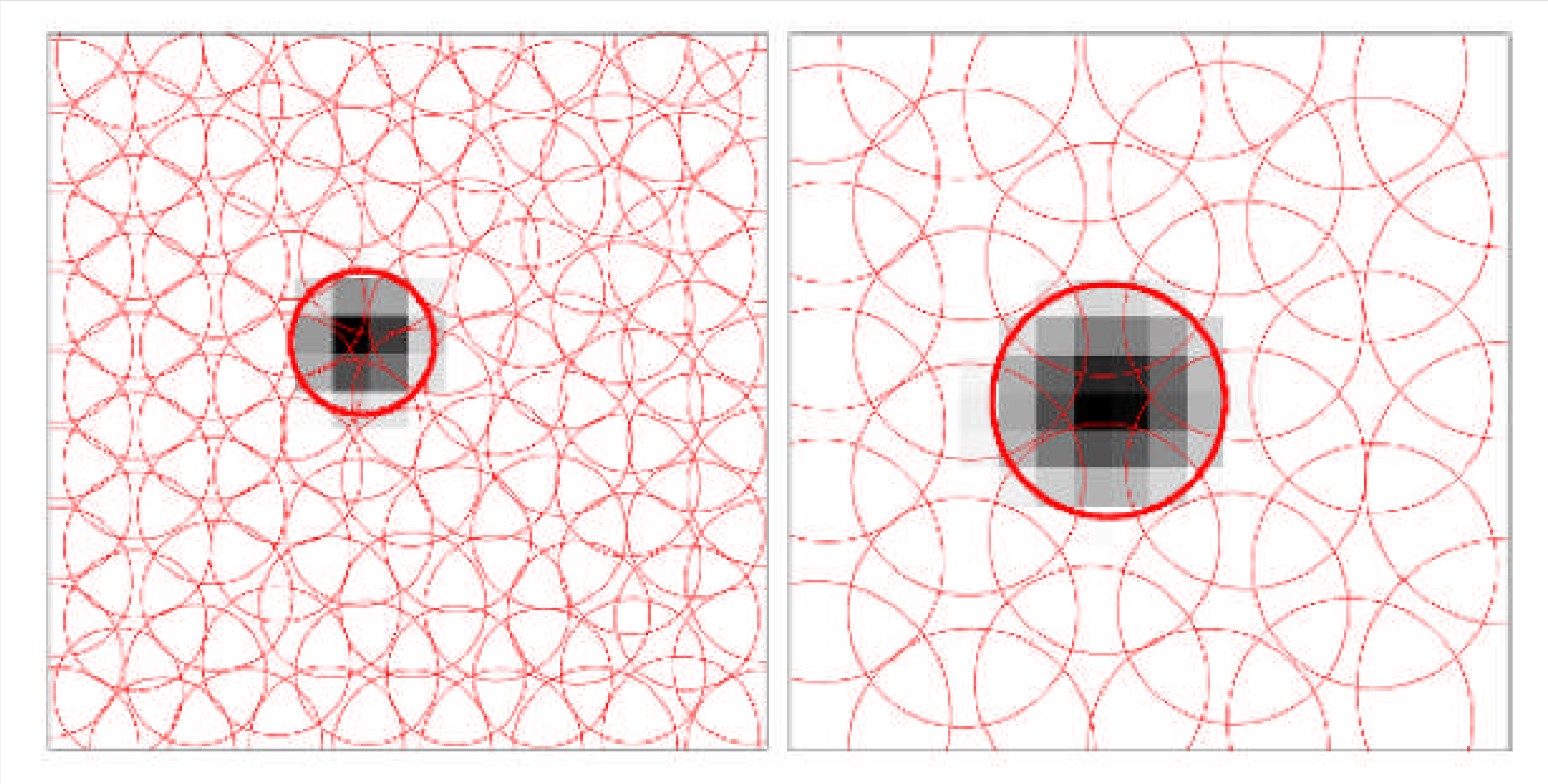
- On color images:



- Many people have gotten this color opponency before, but not in center-surround shape.

Results

- The role of the number of features: 100 versus 32



Results

- The role of λ:

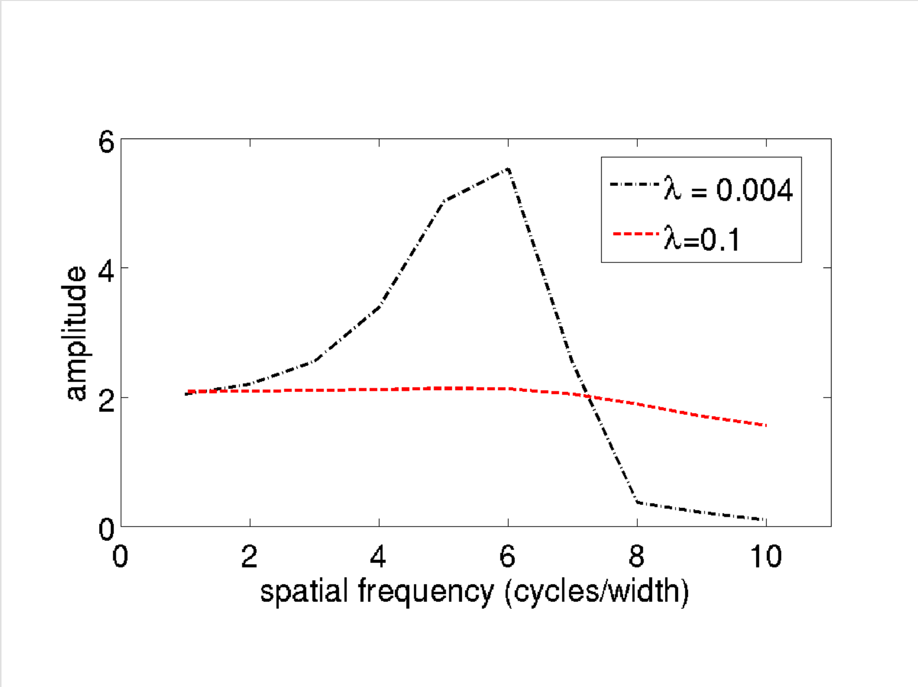
$$E = \left\langle \frac{\|\mathbf{x} - \mathbf{A}\mathbf{s}\|_2^2}{2} \right\rangle + \lambda \|\mathbf{A}\|_1$$

- Recall this reduces the connections…

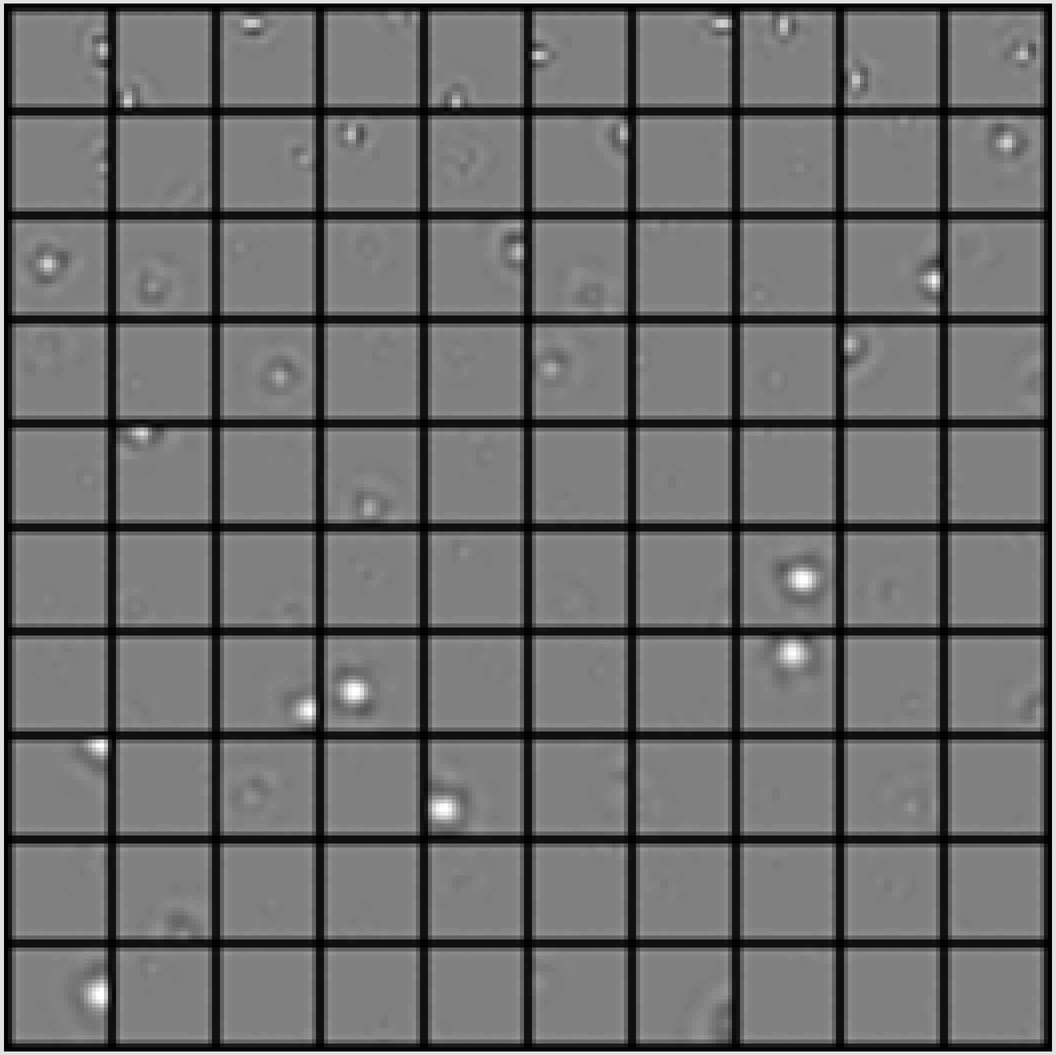
Results

- The role of λ: higher λ means fewer connections, which alters the contrast sensitivity function (CSF).

- Matches recent data on malnourished kids and their CSF's: lower sensitivity at low spatial frequencies, but slightly better at high than normal controls…

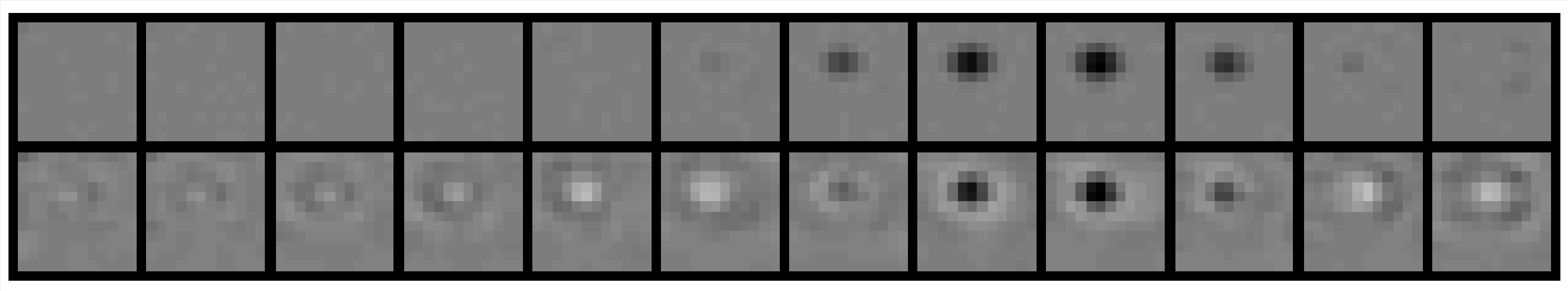


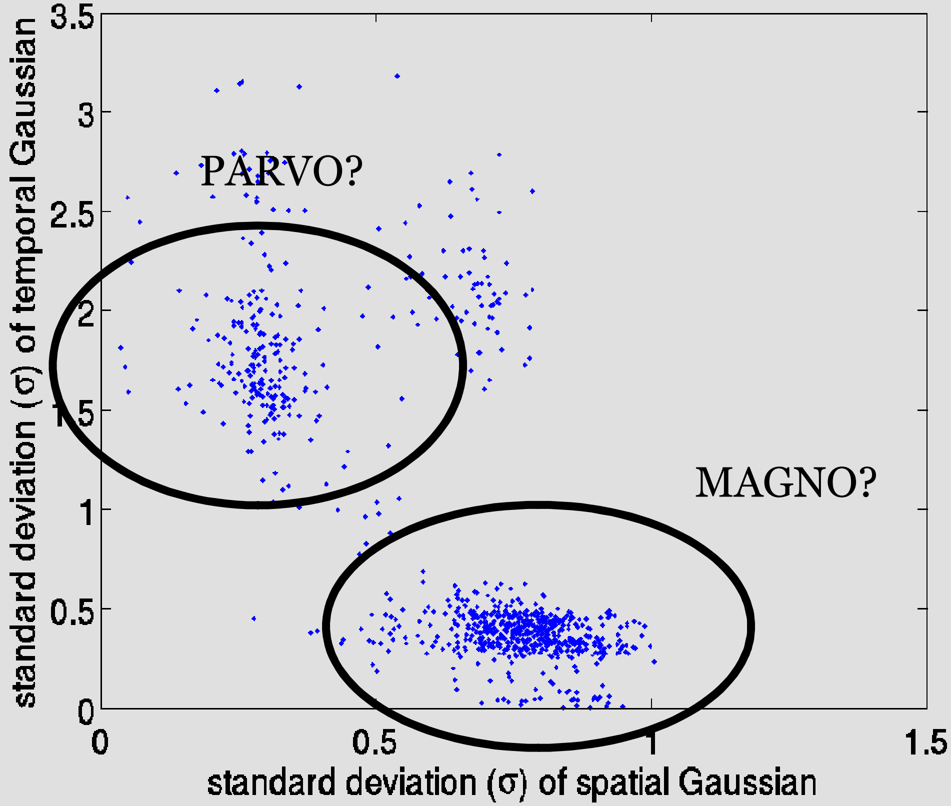
Trained on grayscale video…



Results

- On grayscale video:

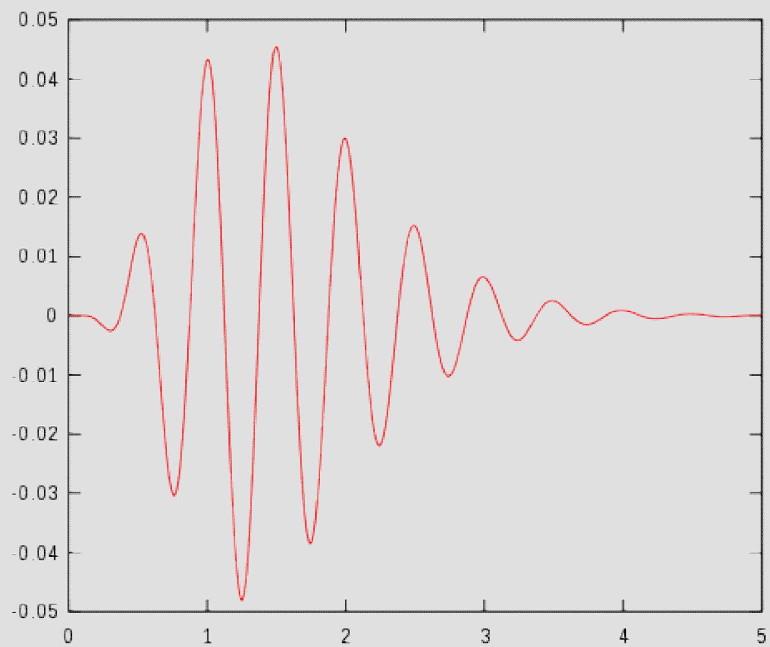




This suggests that these cell types exist *because* they are useful for efficiently encoding the temporal dynamics of the world.

Speech

- Smith & Lewicki showed that Independent Components Analysis (ICA) could be used to explain the gammatone filters in audition:

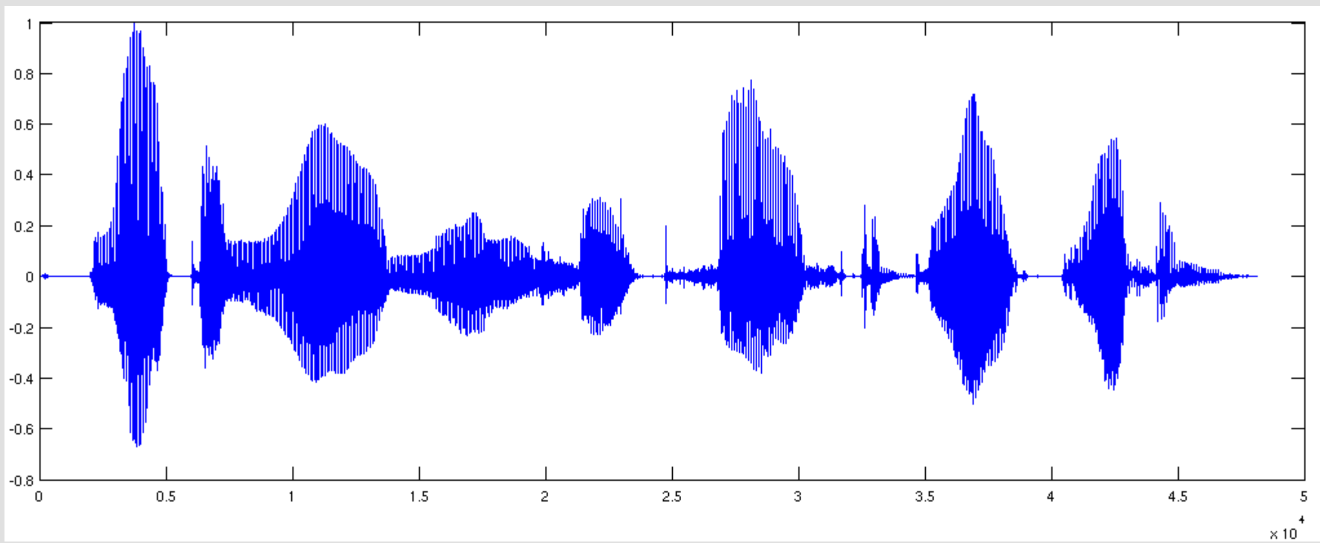


Speech

- (Olshausen & O'Connor, 2002) wondered:
- Why would the brain use the same strategy for preprocessing at a *pre-cortical stage* in the auditory pathway and an *early cortical stage* in the visual pathway?
- Put another way:
  - ICA can explain account for V1 cells in vision - but not retinal ganglion cells.
  - Why would it be used for the processing layer corresponding to retinal ganglion cells in audition???

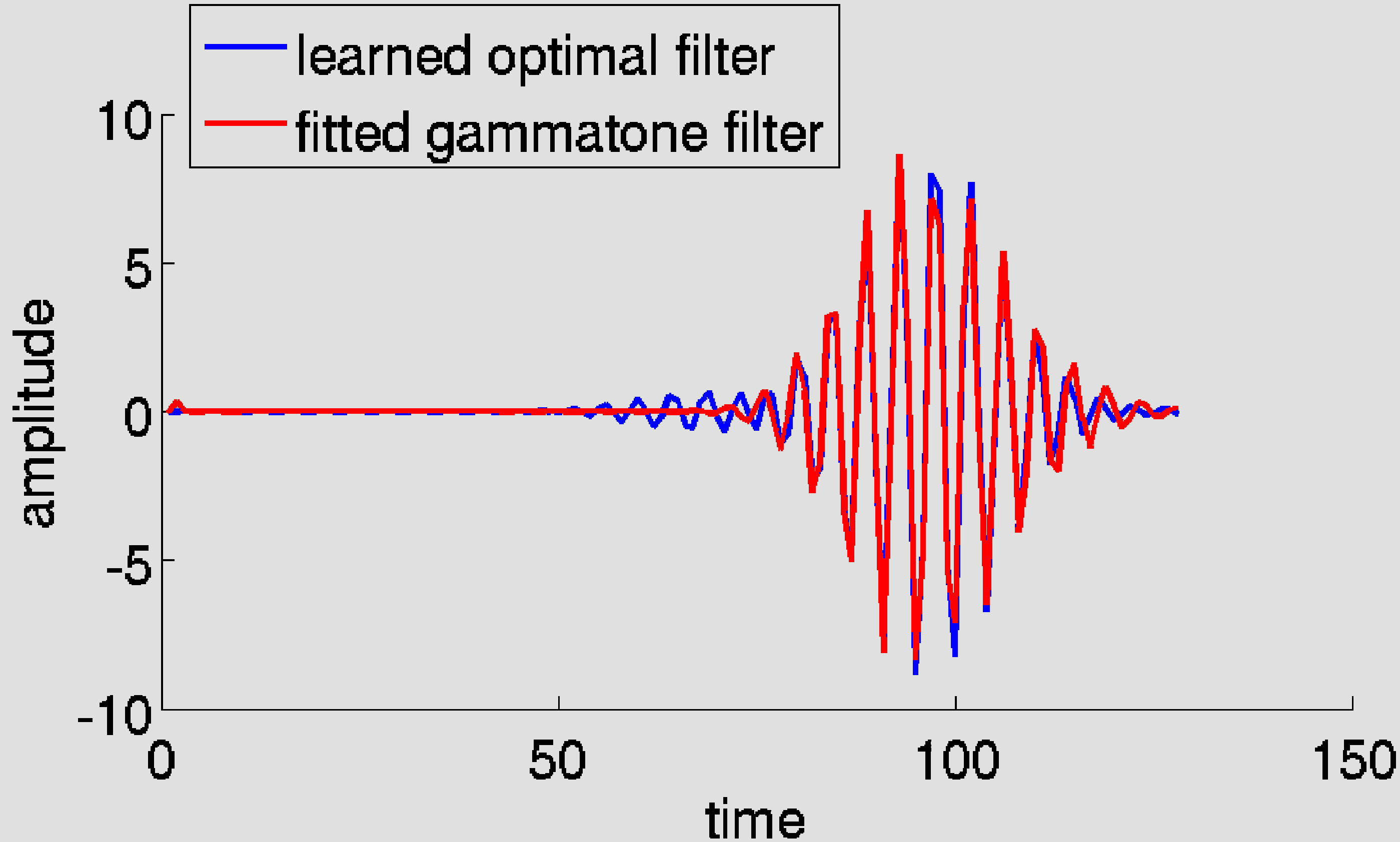
Speech

- The TIMIT dataset contains recordings of 630 speakers of eight major dialects of American English, each reading ten phonetically rich sentences, recorded as 16-bit, 16kHz speech waveform files. E.g., "*Rock n' roll music has great rhythm*":



Speech

- Using exactly the same algorithm, applied to speech, environmental sounds, etc.:



So…

- To answer Olshausen's question - you don't need ICA to get gammatone filters.

- SPCA can account for precortical processing in both audition and vision…

Questions?

SIMSTUDENT IN 10 YEARS

MODELING AND REACTING TO THE STUDENT'S PROBLEM-SOLVING PROCESS

GEOFF GORDON *MACHINE LEARNING DEP'T, CMU*

with thanks to

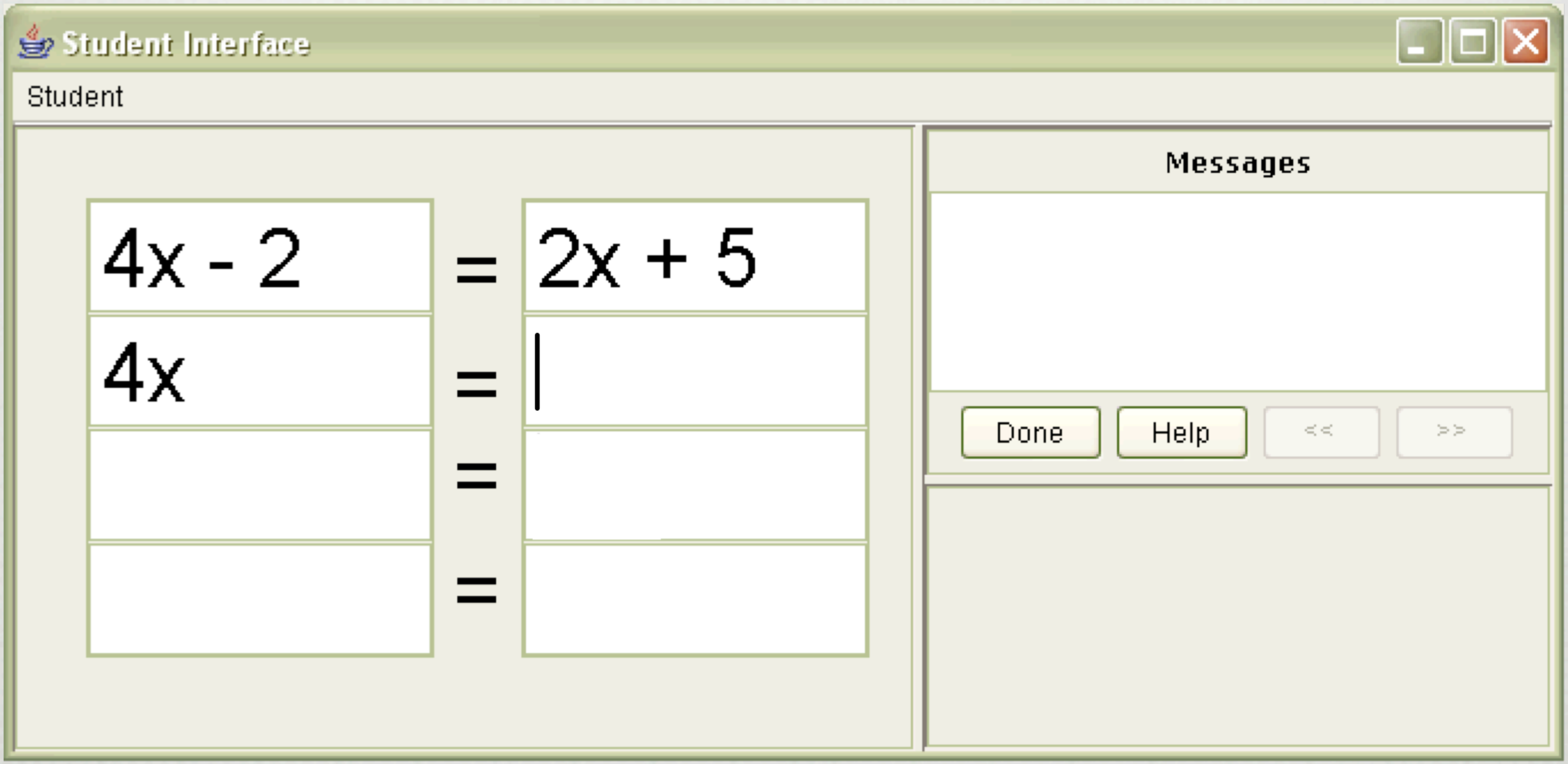
NOBORU MATSUDA *HCII, CMU*

KEN KOEDINGER *HCII, CMU*

NAN LI *CS, CMU*

WILLIAM COHEN *MLD, CMU*

A Cognitive Tutor for Equation solving



Cognitive Model

Solves problems and learns—in the many ways students can

$$3(2x - 5) = 9$$

$$6x - 15 = 9 \qquad 2x - 5 = 3 \qquad 6x - 5 = 9$$

Cognitive Model

Solves problems and learns—in the many ways students can

$$3(2x - 5) = 9$$

If goal is solve a(bx+c) = d
Then rewrite as abx + ac = d

If goal is solve a(bx+c) = d
Then rewrite as bx+c = d/a

If goal is solve a(bx+c) = d
Then rewrite as abx + c = d

skills

bug

$$6x - 15 = 9 \qquad 2x - 5 = 3 \qquad 6x - 5 = 9$$

Cognitive Model

Solves problems and learns—in the many ways students can

$3(2x - 5) = 9$

If goal is solve a(bx+c) = d
Then rewrite as abx + ac = d

If goal is solve a(bx+c) = d
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If goal is solve a(bx+c) = d
Then rewrite as abx + c = d

skills

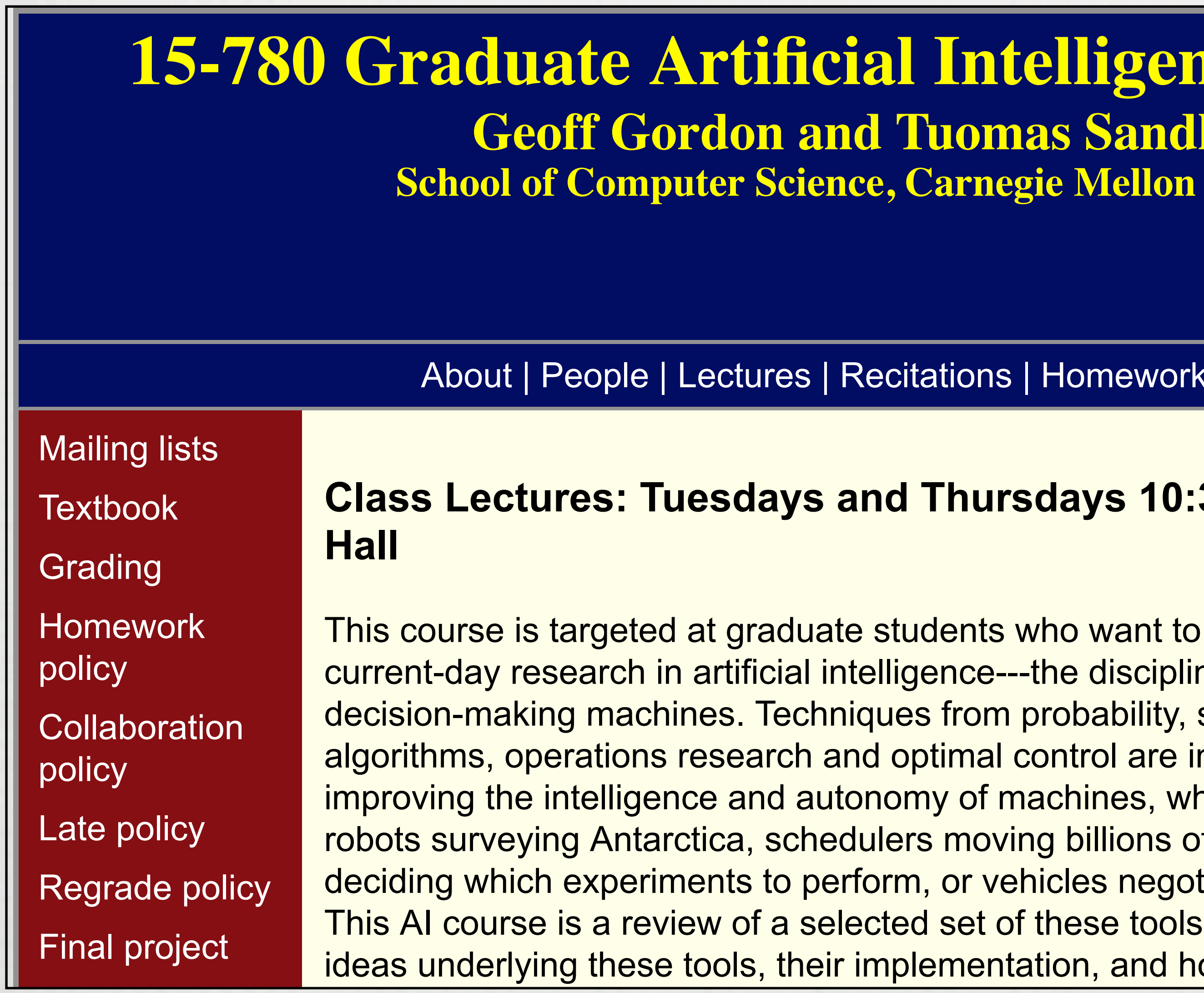
bug

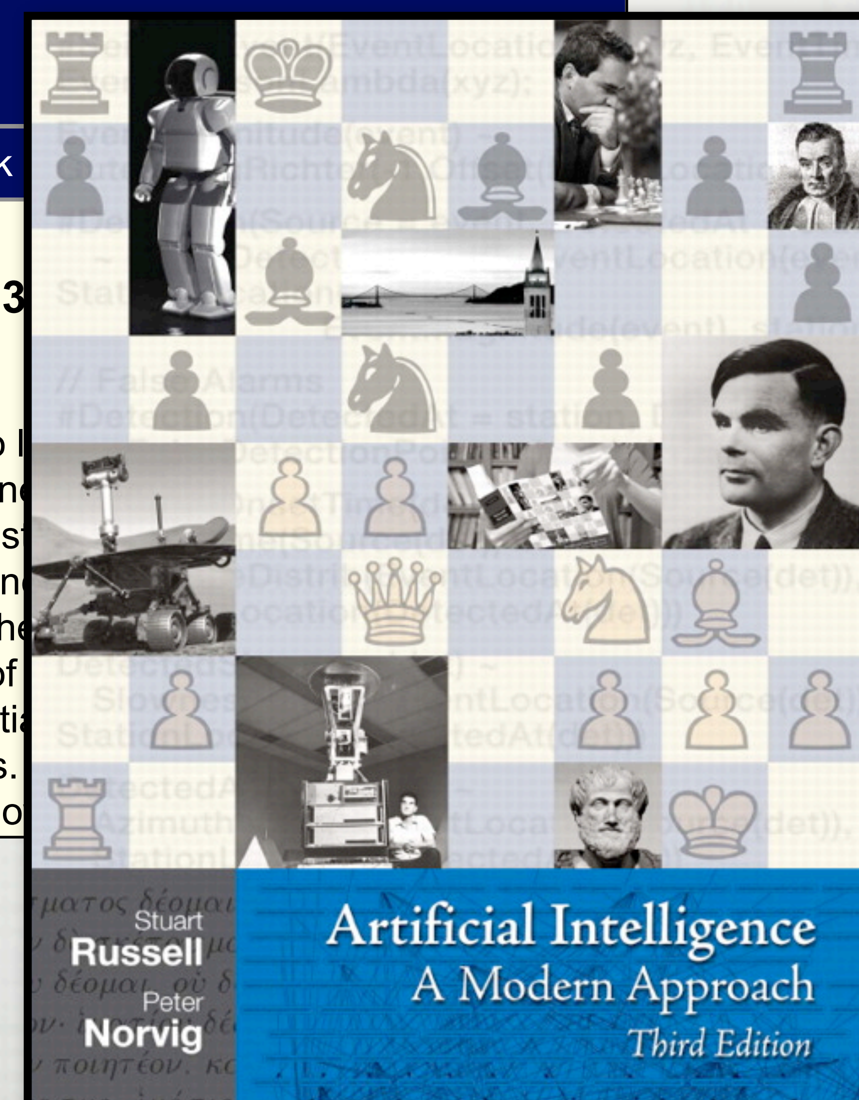
$6x - 15 = 9$ $\quad$ $2x - 5 = 3$ $\quad$ $6x - 5 = 9$

- Model Tracing: follow students through individual approaches to problem
⇒ context-sensitive feedback

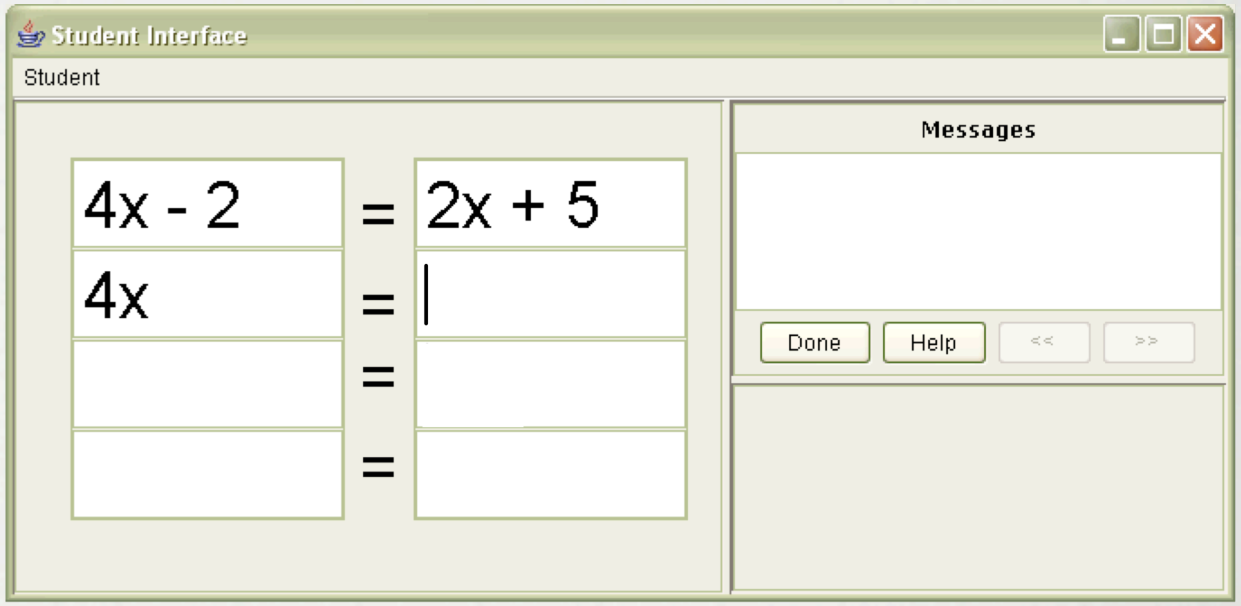
What does model look like?

What does model look like?





SimStudent model

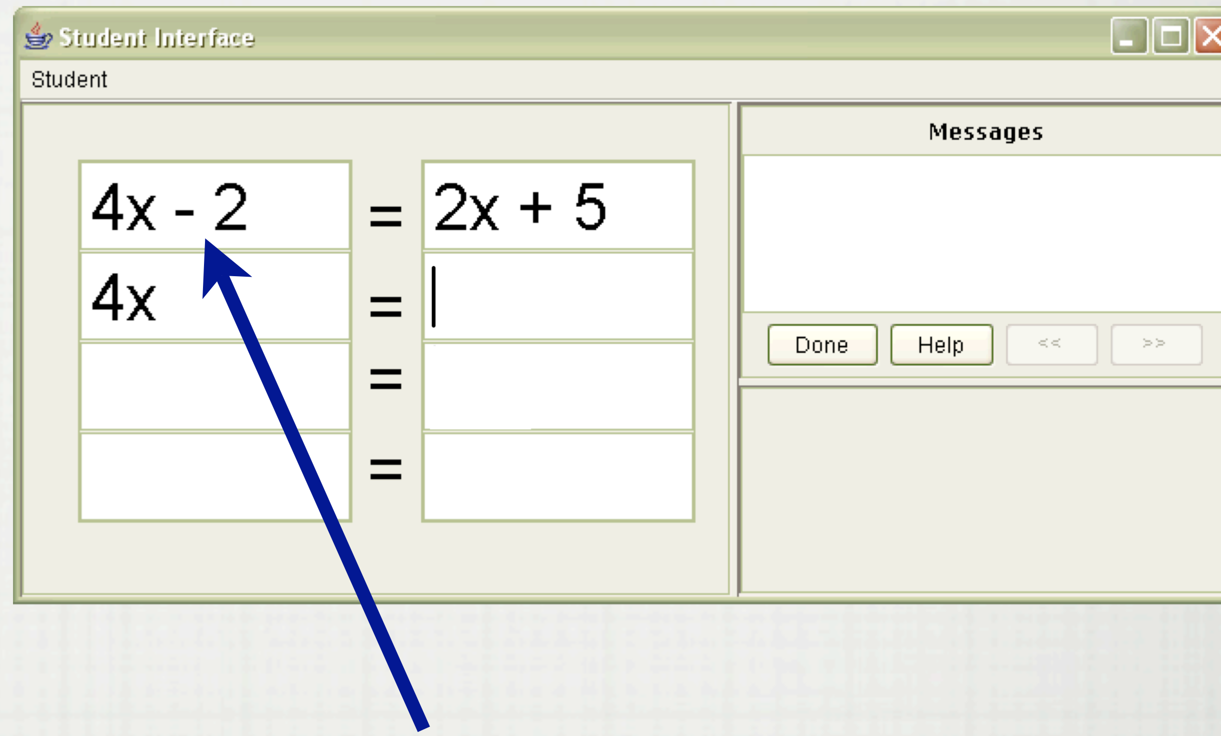


- Declarative knowledge
- Perception
- Production rules
- Learning

[Matsuda et al.], based on ACT-R [Anderson et al.]

SIMSTUDENT MODEL

- ☐ Declarative knowledge
- ☐ Perception
- ☐ Production rules
- ☐ Learning

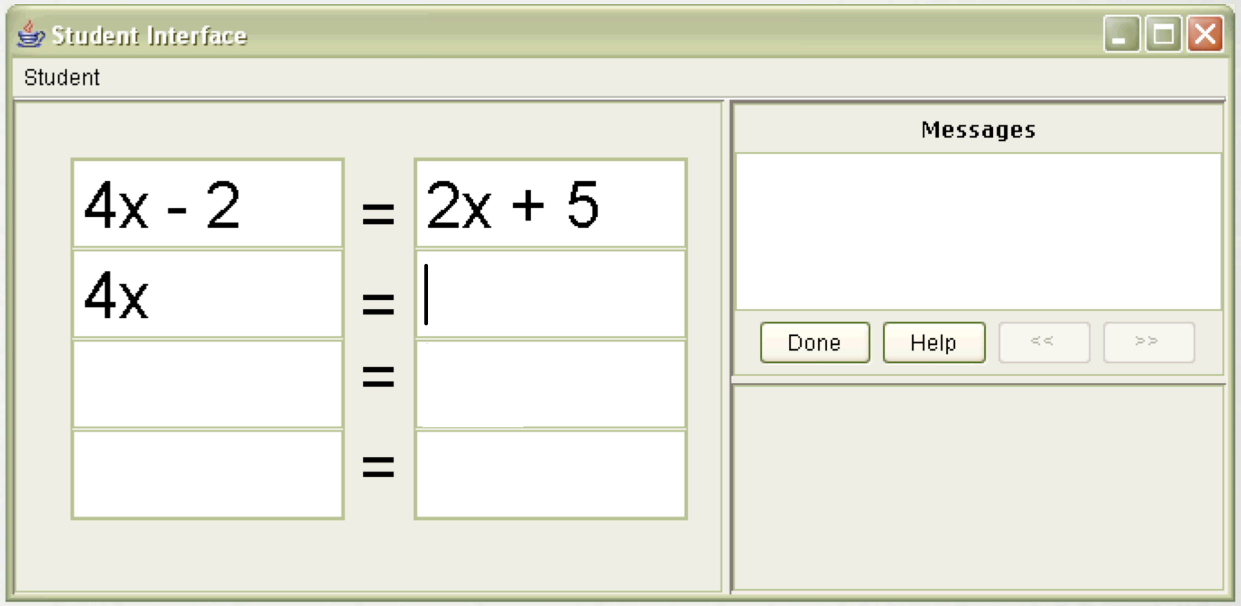



```
(cell
  (value “4x - 2”))
```

[Matsuda et al.], based on ACT-R [Anderson et al.]

SIMSTUDENT MODEL

- Declarative knowledge
- Perception
- Production rules
- Learning



SIMSTUDENT MODEL

- Declarative knowledge
- Perception
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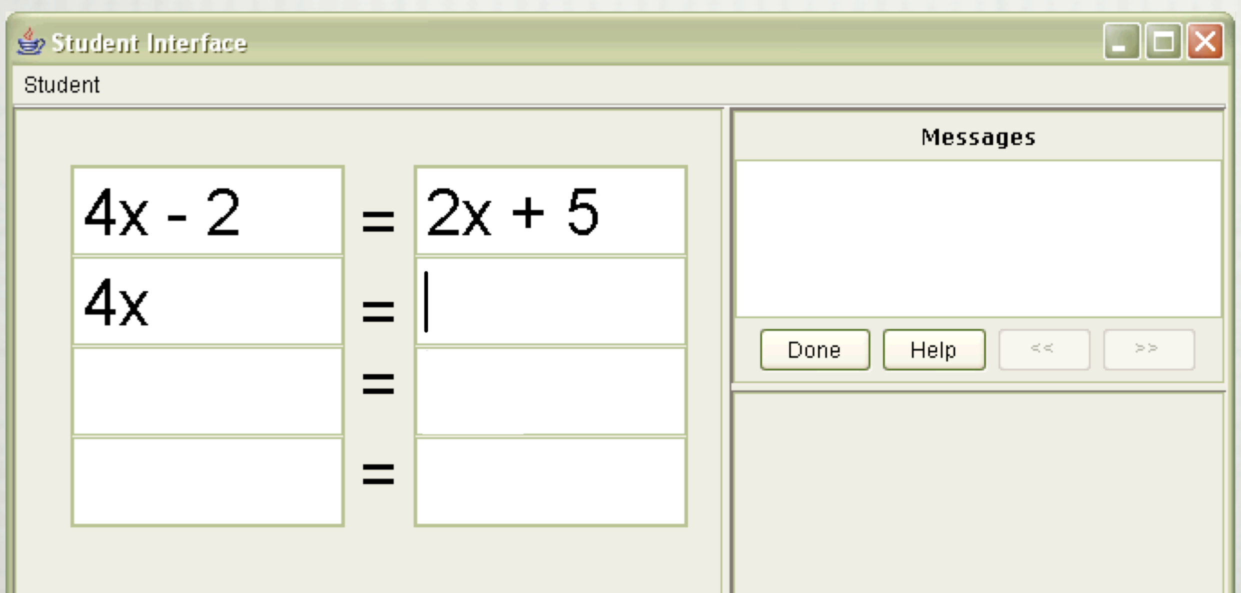
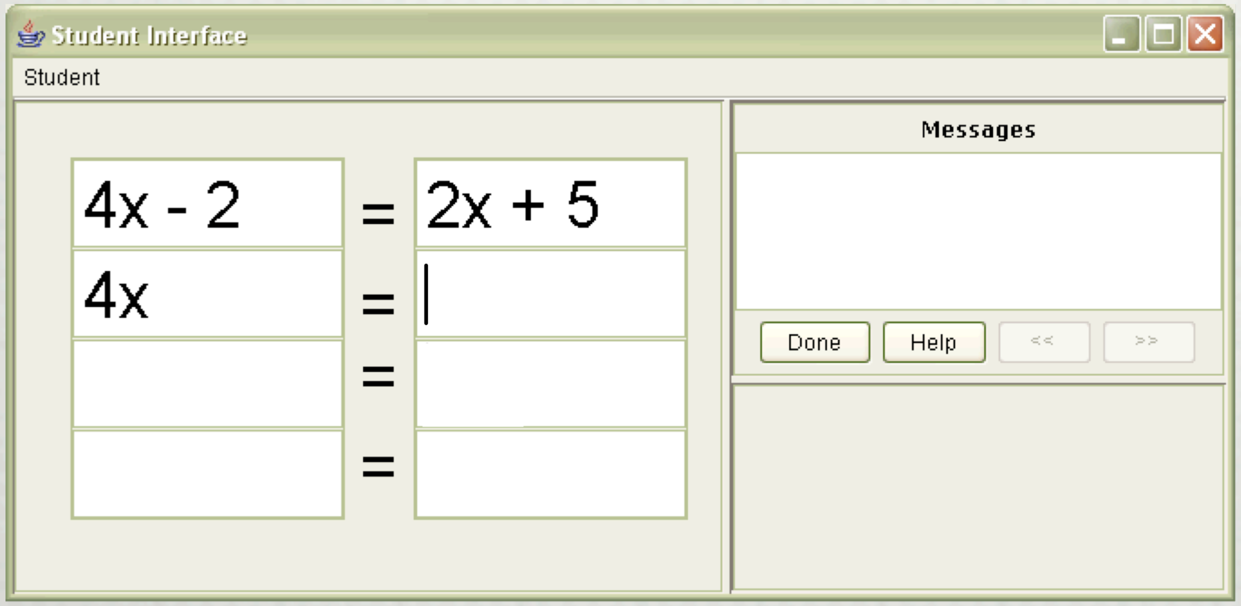


SimStudent model

- ☐ Declarative knowledge
- ☐ Perception
- ☐ Production rules
- ☐ Learning

```
(problem
  (interface-elements
    (table
      (column
        (cell
          (value "4x - 2"))
        (cell
          (value "4x"))
          ...)
      (column
        (cell
          (value "2x + 5"))
        (cell
          (name "selection")
          (value ""))
        ...)))
```



SimStudent model

- Declarative knowledge
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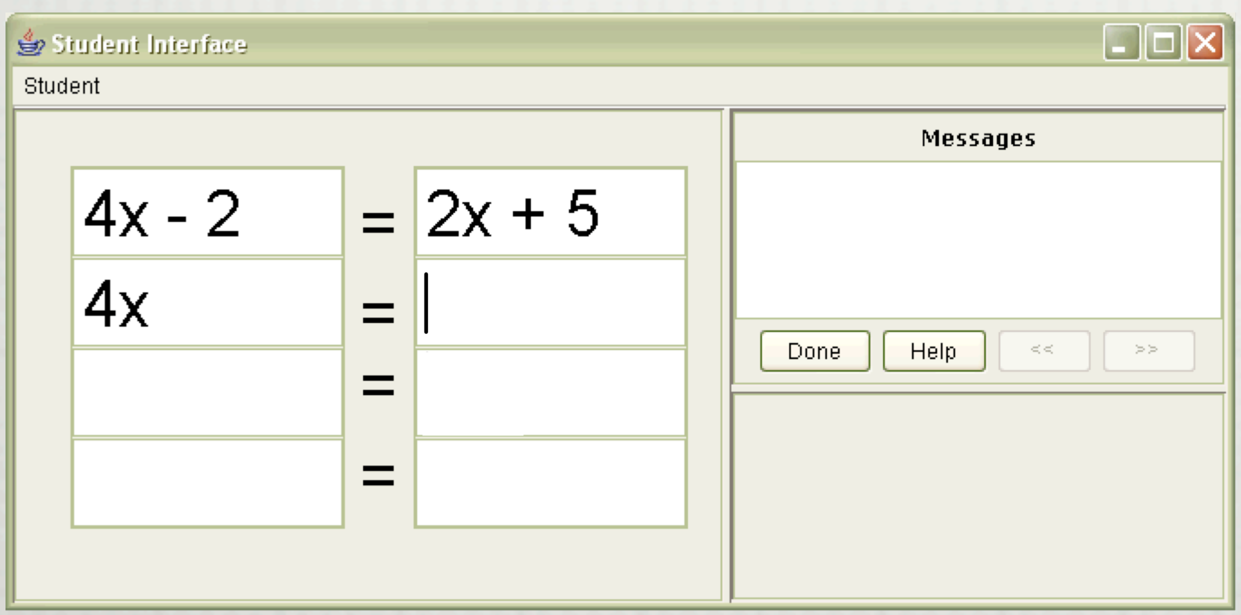
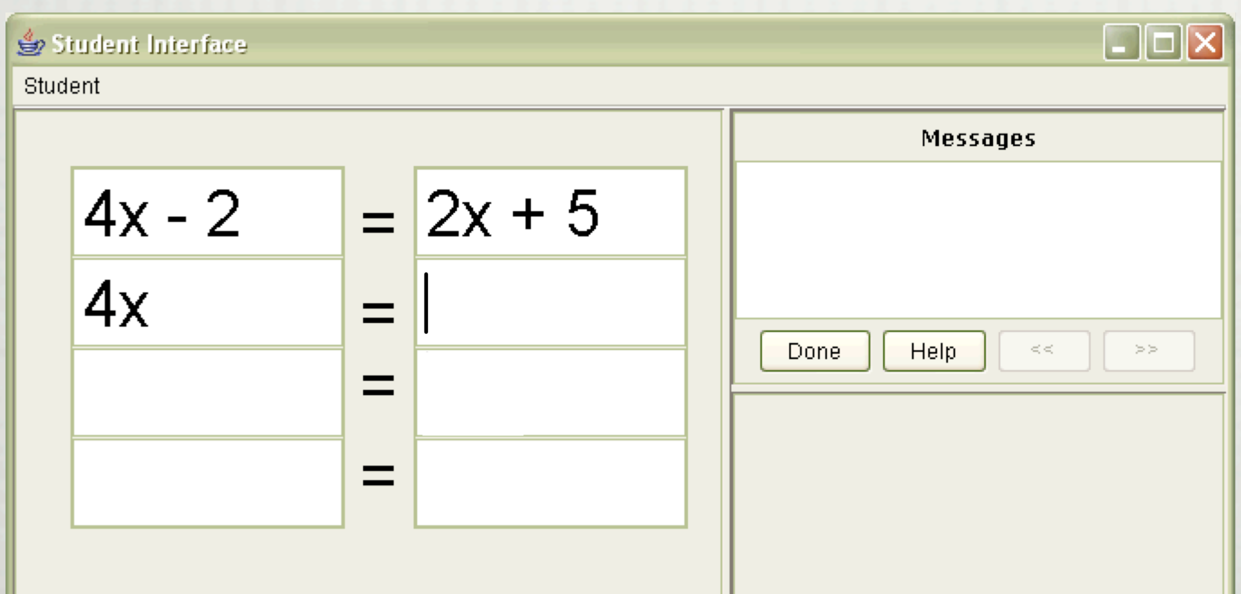


SimStudent model

- Declarative knowledge
- Perception
- Production rules
- Learning

what	***If*** (a structure in WM)
when	***satisfies*** (constraints)
how	***then do*** (action)



SimStudent model

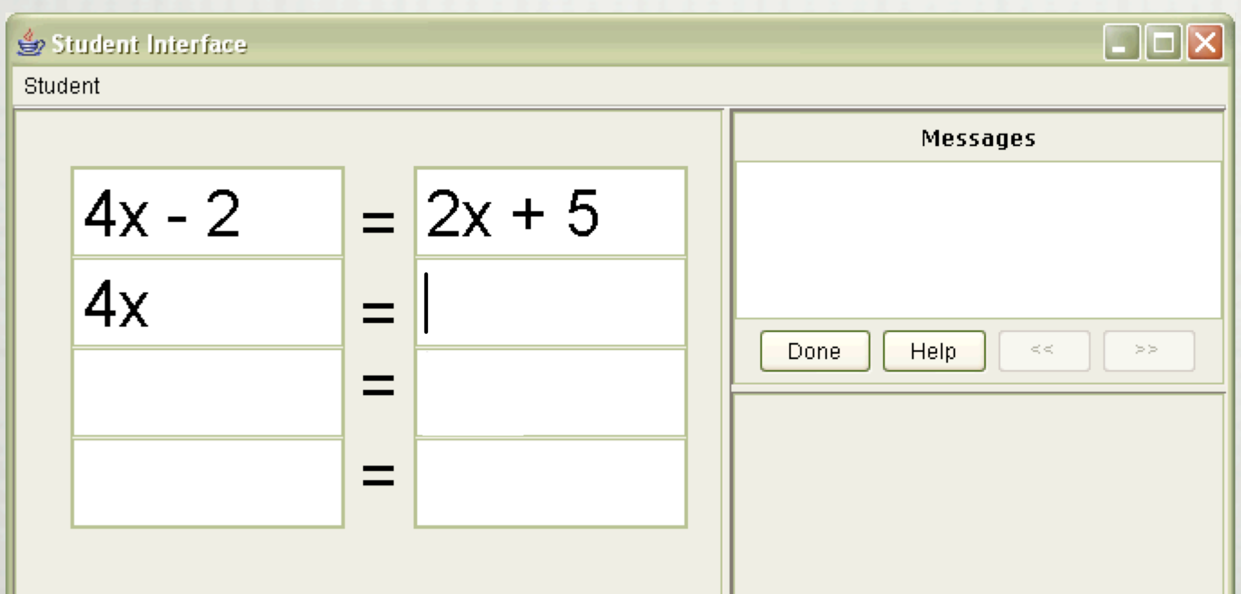
- ☐ Declarative knowledge
- ☐ Perception
- ☐ Production rules
- ☐ Learning

what	***If*** (a structure in WM)
when	***satisfies*** (constraints)
how	***then do*** (action)

```
(table
  (column
    (cell
      (value ?x))

(constant-term ?x ?c)
(non-null ?c)

(enter (subtract ?x ?c) ...
(enter (subtract ?z ?c) ...
```



SimStudent model

- Declarative knowledge
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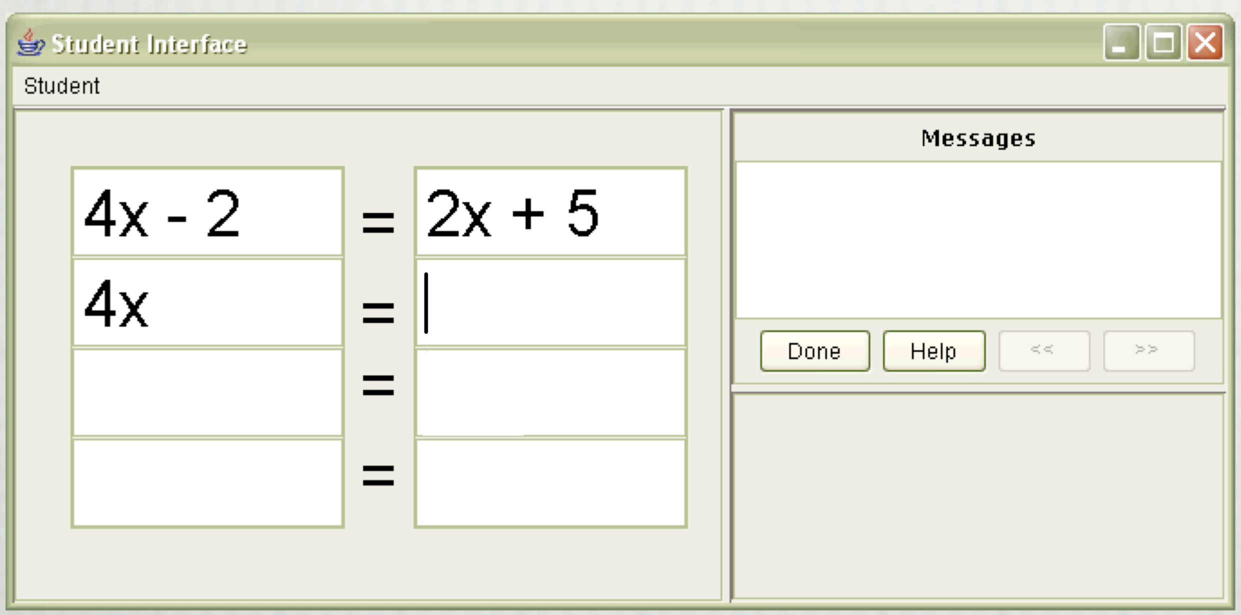


what

```
(table
  (column
    (cell
      (value ?u:string))
    ?v:cell
    ?*)
  (column
    (cell
      (value ?z:string))
    ?w:cell
    ?*))
```

when

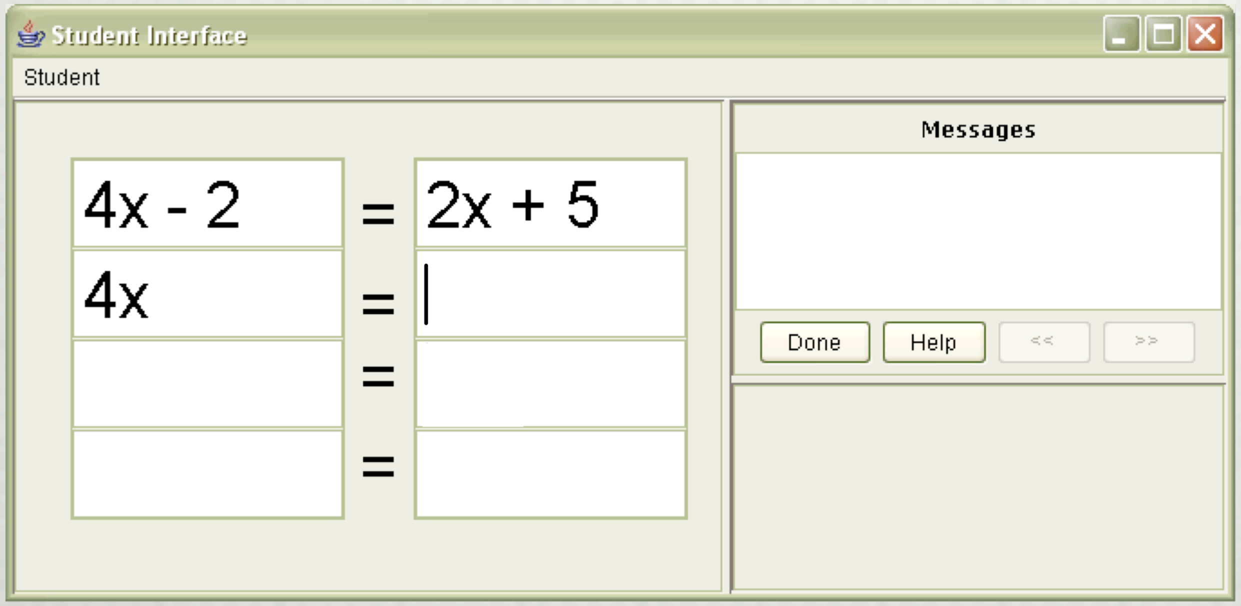
```
(constant-term ?u ?c)
(non-null ?c)
==>
```

how

```
(enter (subtract ?u ?c) ?v)
(enter (subtract ?z ?c) ?w)
```

SimStudent model

- Declarative knowledge
- Perception
- Production rules
- Learning



Types of Learning

- Natural learning
  - by student
- Simulated learning
  - by SimStudent
- Model learning
  - making SimStudent a better model

Types of Learning

- Natural learning
  - by student
- Simulated learning
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  - making SimStudent a better model

"machine learning"

- Machine learning can help us discover detailed, accurate models of how students learn
- Machine learning can also be part of our models

Types of Learning

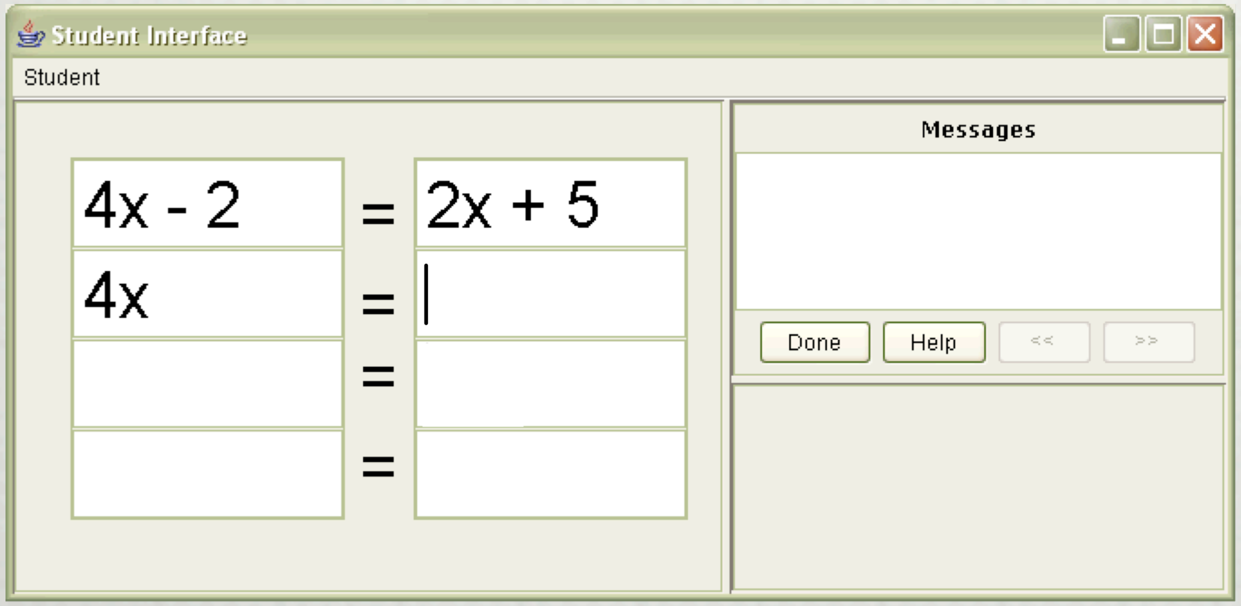
- Natural learning
  - by student
- Simulated learning
  - by SimStudent
- Model learning
  - making SimStudent a better model

"machine learning"

- Machine learning can help us discover detailed, accurate models of how students learn
- Machine learning can also be part of our models

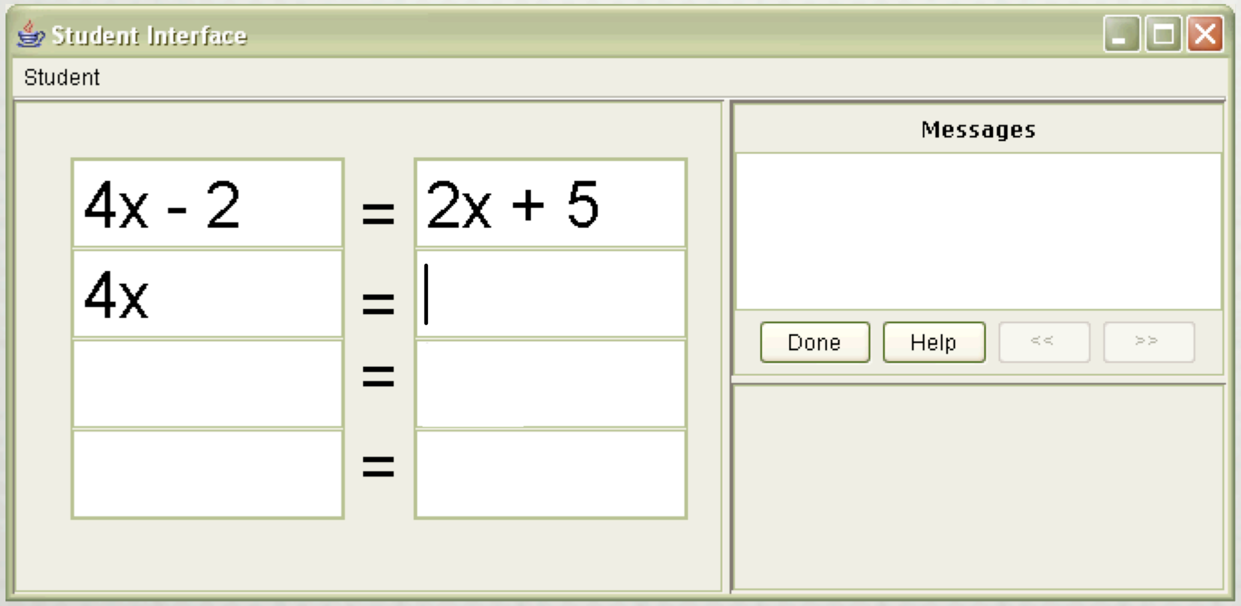
SIMSTUDENT MODEL

- ☐ Declarative knowledge
- ☐ Perception
- ☐ Production rules
- ☐ Learning



SIMSTUDENT MODEL

- Declarative knowledge $\Leftarrow$ chunks, types, features
- Perception $\Leftarrow$ low-level knowledge to high-level
- Production rules $\Leftarrow$ rule learning
- Learning



SimStudent model

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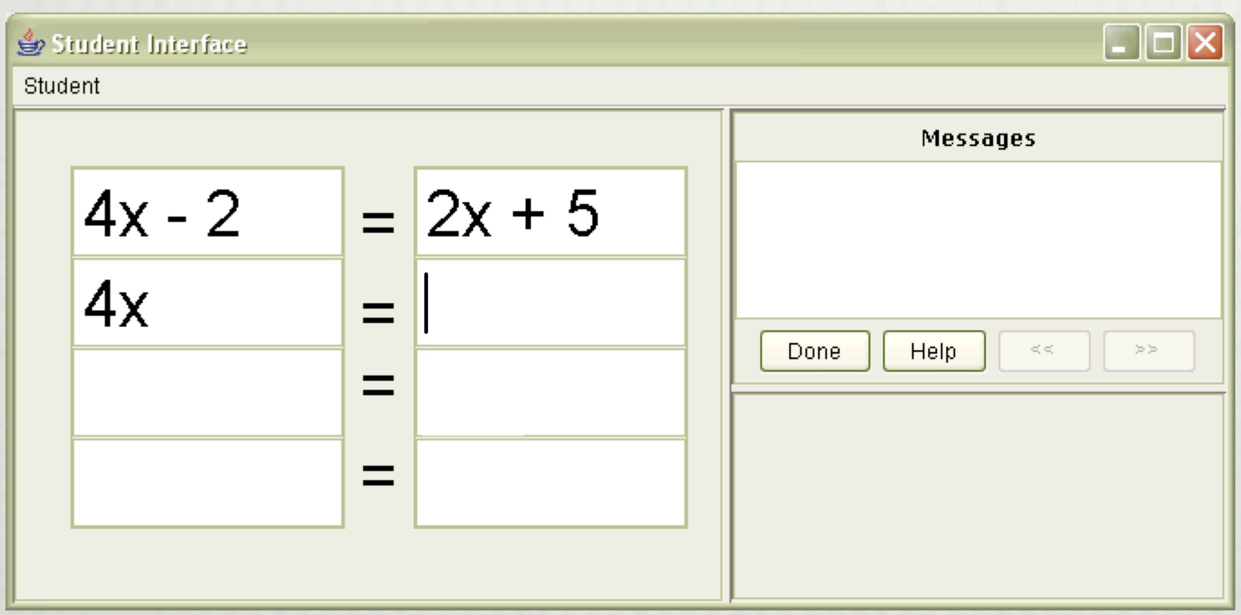

SimStudent Learning

- ***Inductive Logic Programming*** (ILP)
  - from worked examples: Programming by Demonstration
  - trial and error w/ immediate feedback: Tutored Problem Solving
- Mixture of several algorithms:
  - Version space [Mitchell] for ***what***
  - FOIL [Quinlan] for ***when***
  - “most specific generalization” for ***how***

SimStudent: Results

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  - e.g., so that model tracing works well

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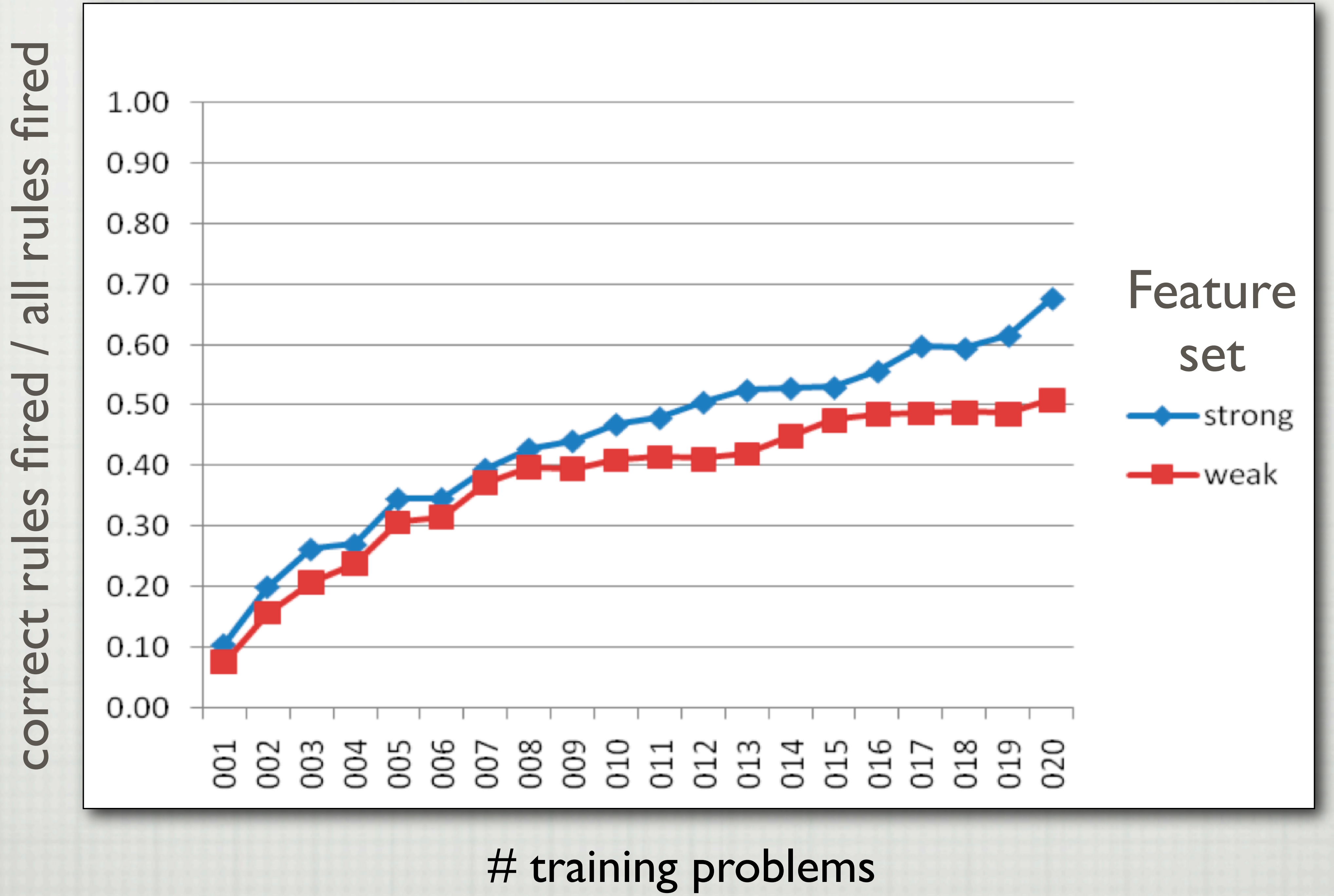
SIMSTUDENT: RESULTS

- Does SimStudent learn ***good rule sets***? **Yes**
  - e.g., so that model tracing works well
- Does SimStudent learn rules ***like real students do***? ***Maybe***
  - in the right order, with the right amount of training data, making similar mistakes along the way
- Study:
  - SimStudent solves a sequence of training problems
  - Learns new rules after each one
  - Use test set of problems to evaluate rules learned

SimStudent: Test set performance



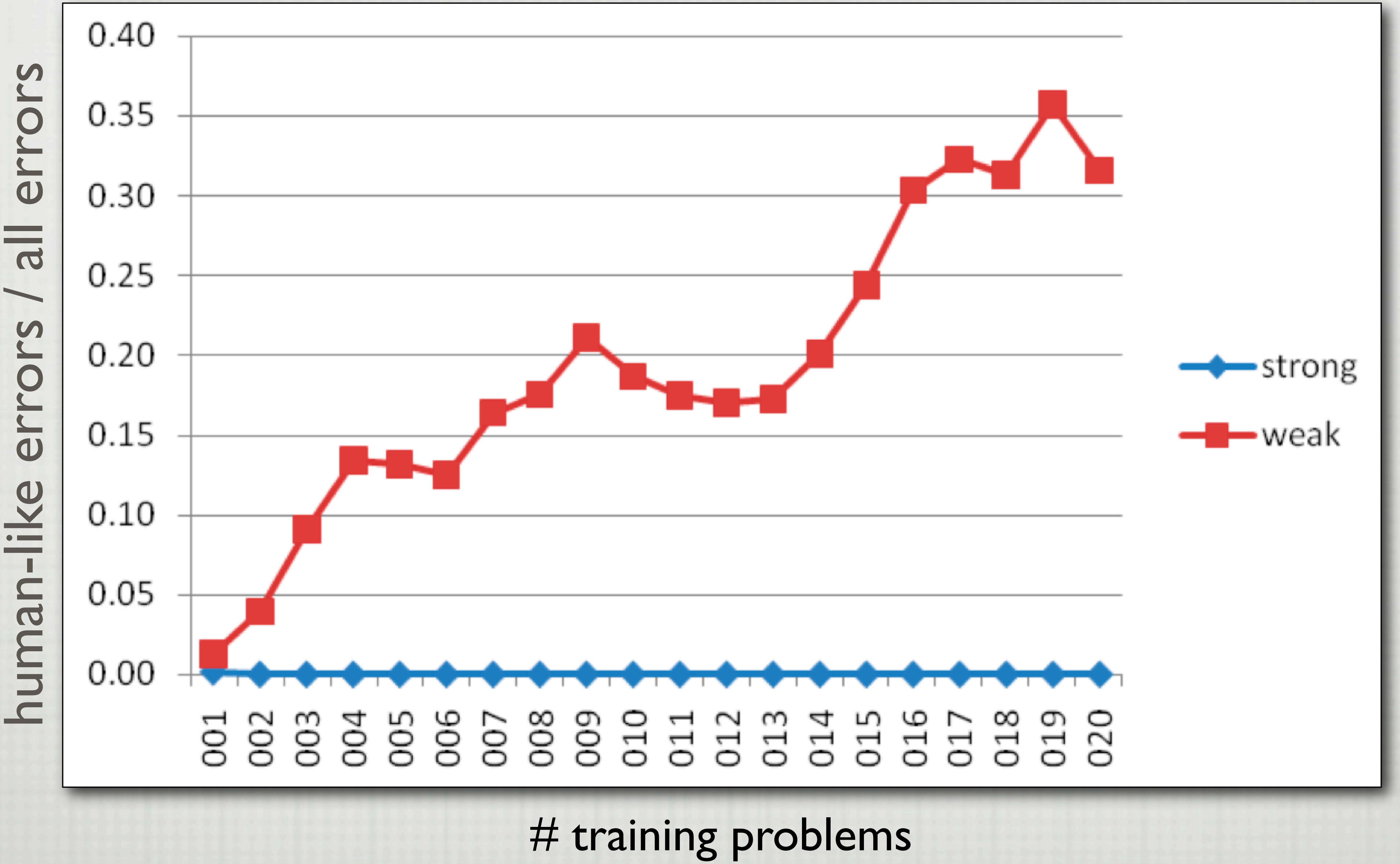
SimStudent: weak feature set human-like errors

Error Schema	Problem Schema	Freqency
add B	A = B + C*v*	55
add A	-A*v*+B = C	52
add A	A-B*v* = C	44
add C	Av+B = C	23
add C	Av+B = -C	23
add A	-A = B+C*v*	22
subtract A	-A+B*v* = C	20
subtract A	-A*v*+B = C	20
divide A	*v*/A = B	14
multiply A	A/*v* = B	11
multiply A	A*v* = B	2
subtract C	A*v*+B = -C	1
subtract A	A = B*v*+C	1

$$3 = 5 + 2x$$
$$\not\Rightarrow 8 = 2x$$

- Also some non-human-like errors

SimStudent: strong feature set
fewer errors, but not human-like



Where do features come from?

- SimStudent performance depends strongly on feature set
  - but SimStudent says nothing about where features comes from
- We should expand scope of model to capture new interesting area: how does student acquire features?
- Perhaps to make human-like errors we need to learn features ***at the same time as*** rules
- Instance of larger problem: ***not enough learning***

THE FUTURE

The Future

- Unified model of student's rule learning, feature learning, and problem solving

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  - worked example: explained better by candidate rule A or rule B?

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The Future

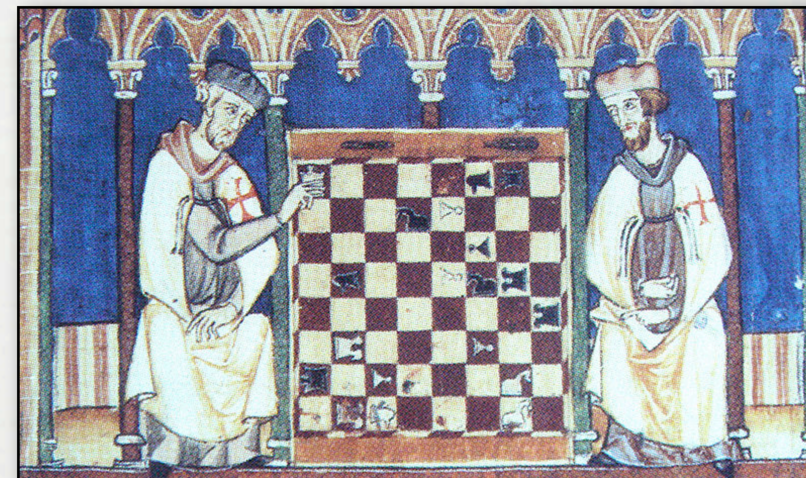
- Unified model of student's rule learning, feature learning, and problem solving
- Rule learning = reasoning about probabilities
  - … e B?

> One of the main tenets of ACT-R is that human cognition represents the probabilistic nature of the environment and … is Bayesian in nature.
>
> [Sanner, Anderson, Lebiere, Lovett, 2000]

  - am I more likely to succeed by applying rule A or rule B?
- Perception, cognition, and action are all part of an intertwined statistical reasoning problem

Example: Board Games

- Chess: deep search + pattern recognition
  - humans have excellent pattern recognition (snap evaluation of position strength)
  - else, could not match Deep Blue, which considers $10^8 \times$ more positions
- Backgammon: even more pattern recognition
  - top humans and computers use shallow search (a few ply)



- In both games: difficult statistical learning problem (with highly delayed and noisy feedback!) embedded in rule selection problem

REPRESENTATION

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- "Logical production systems" do not support statistical reasoning
  - nor do certainty factors, nonmonotonic logic, fuzzy logic, …
  - at least, not in a scalable way—this is a lesson of AI 1965–1985
  - to do probabilistic reasoning, we need probabilities!

Representation

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  - nor do certainty factors, nonmonotonic logic, fuzzy logic, …
  - at least, not in a scalable way—this is a lesson of AI 1965–1985
  - to do probabilistic reasoning, we need probabilities!
- What representation can we use?
  - a production system based on ***probabilistic*** logic
  - the same way SimStudent's production system is based on FOL

PROBABILISTIC LOGIC

- Ordinary production rule:
  - if we see ***condition***, conclude ***consequent***
  - condition ***binds variables*** to objects, consequent uses them
- Probabilistic production rule:
  - if we see ***condition***, and ***unseen*** coin(*p*) shows H, conclude ***consequent***
- e.g., Independent Choice Logic [Poole]

```
(table
  (column
    (cell
      (value ?u:string))
    ?v:cell
    ?*)
  (column
    (cell
      (value ?z:string))
    ?w:cell
    ?*))
(constant-term ?u ?c)
(non-null ?c)
==>
(enter (subtract ?u ?c) ?v)
(enter (subtract ?z ?c) ?w)
```

TINY DIFFERENCE MAKES ALL THE DIFFERENCE

- Probabilistic logic ***strictly*** generalizes
  - Ordinary production systems (set p=1)
  - Graphical models (Bayes nets, Markov random fields, …)
  - Markov logic networks
  - Acyclic fragment of FOL
- But at a price
  - in ordinary production system, time for chain of reasoning is ***linear*** in number of rule instances
  - w/o further restrictions, finding consequences of given set of probabilistic rule instances is ***#P-complete***

Further Restrictions

- Simulated learning (= finding new rules and features, improving existing ones)
  - can afford to spend time to approximate the posterior over sets of probabilistic production rules
  - see Proc. NIPS, AISTATS, ICML, …
    - structured SVMs, Latent Dirichlet Allocation, Bayesian PCA, …
  - example in a couple of slides
- Performance (= using existing rules)
  - must be fast! ~100ms per rule
  - must use some drastic restriction and/or approximation

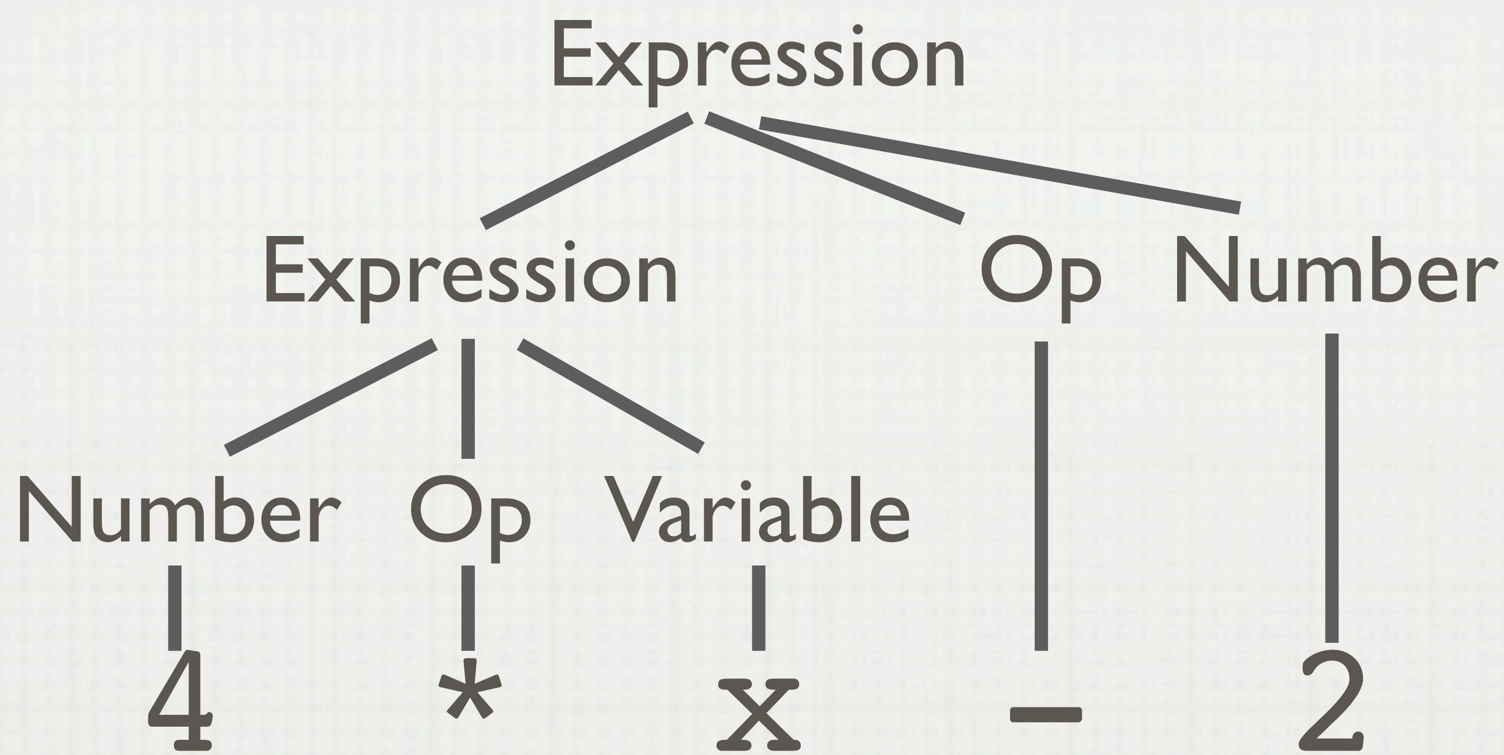
Proposal: Statistical Reasoning at Performance Time

- Small network of ***active productions*** connects small set of ***active propositions***
  - production "firing" in traditional system = becoming "active" here
  - chunks in WM in traditional system = "active" propositions here
  - WM now a ***distribution*** over active prop'ns (v. activation level)
- MCMC (e.g., Gibbs sampling, particle filter) within active network
  - initial conclusions fast, improve with deliberation
  - reduces to traditional handling of productions when $p \rightarrow 1$
- When active network gets too big, prune
  - replace a portion of network with statistics from recent samples

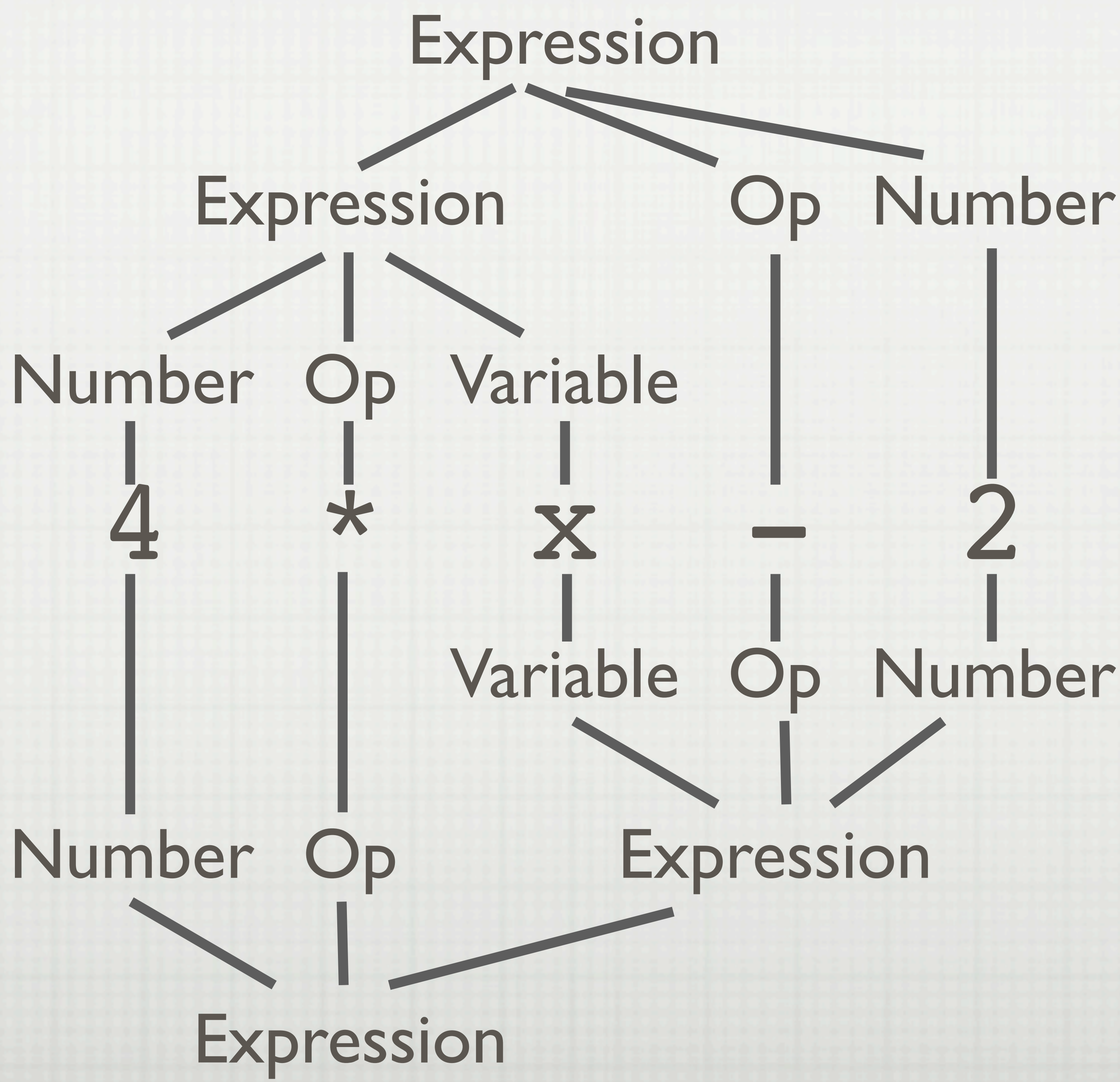
Example of Active Network

```
4   *   x   -   2
```

Example of Active Network



Example of Active Network



THE CASE FOR BAYES: CLASSICAL CONDITIONING

Neutral stimuli: A, X (e.g., bell, light, buzzer)

Elicits involuntary response: US (e.g., shock)

Effect name	2nd-order conditioning	Conditioned inhibition
A-X trials	few	many
A-US trials	many	many
test: X predicts US?	↑	↓

- Only fully Bayesian inference/learning was able to capture both effects [Courville, Daw, Gordon, Touretzky, NIPS 2003]
- With few A-X trials, animal learns 1 "rule": (A, X, US) all associated
- With more, animal learns 2 "rules": (A, X, no US) v. (A, US, no X)

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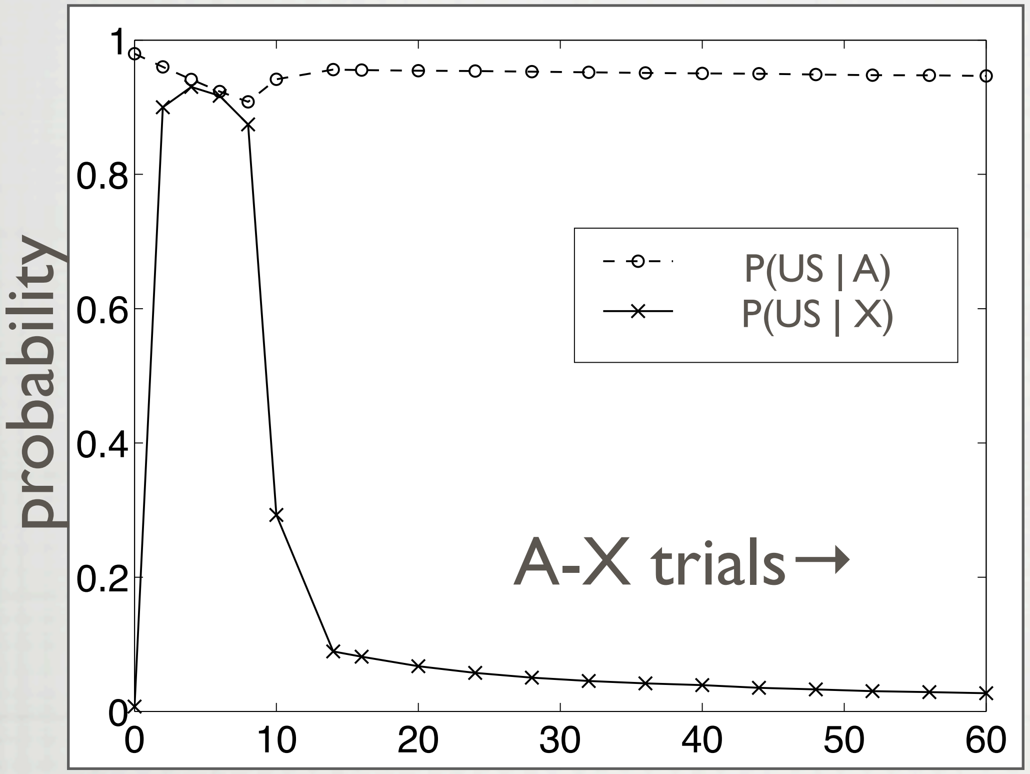

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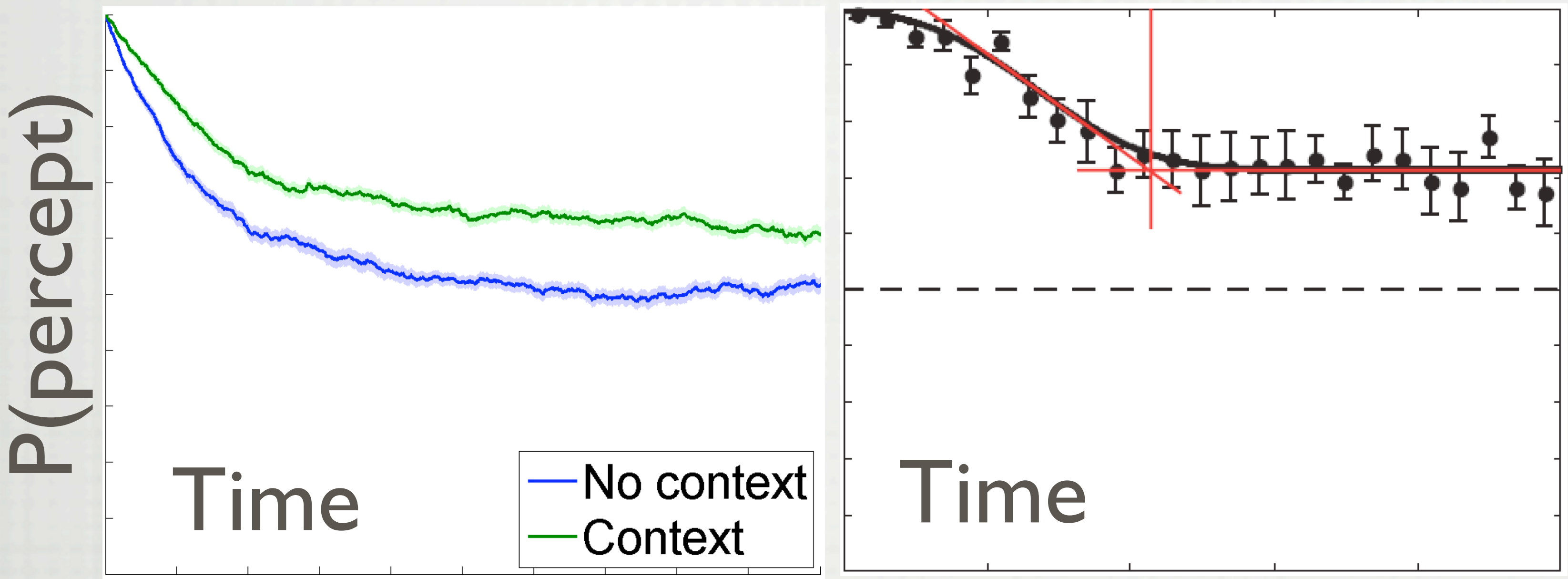
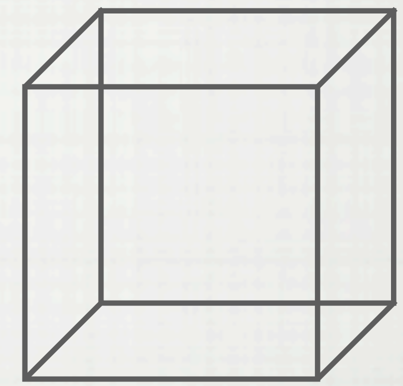
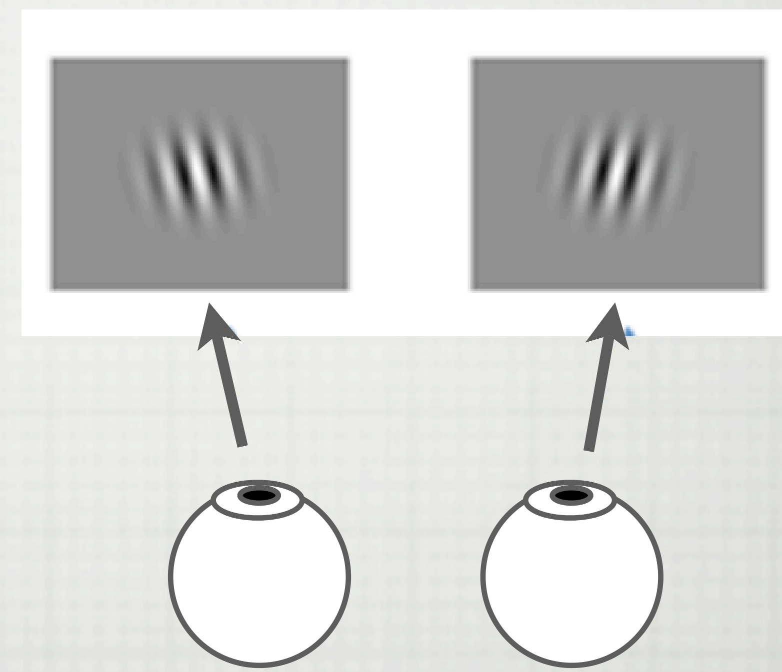
BISTABLE PERCEPTS, BINOCULAR FUSION, AND GIBBS SAMPLING







[Gershman, Vul, Tenenbaum, 2009]

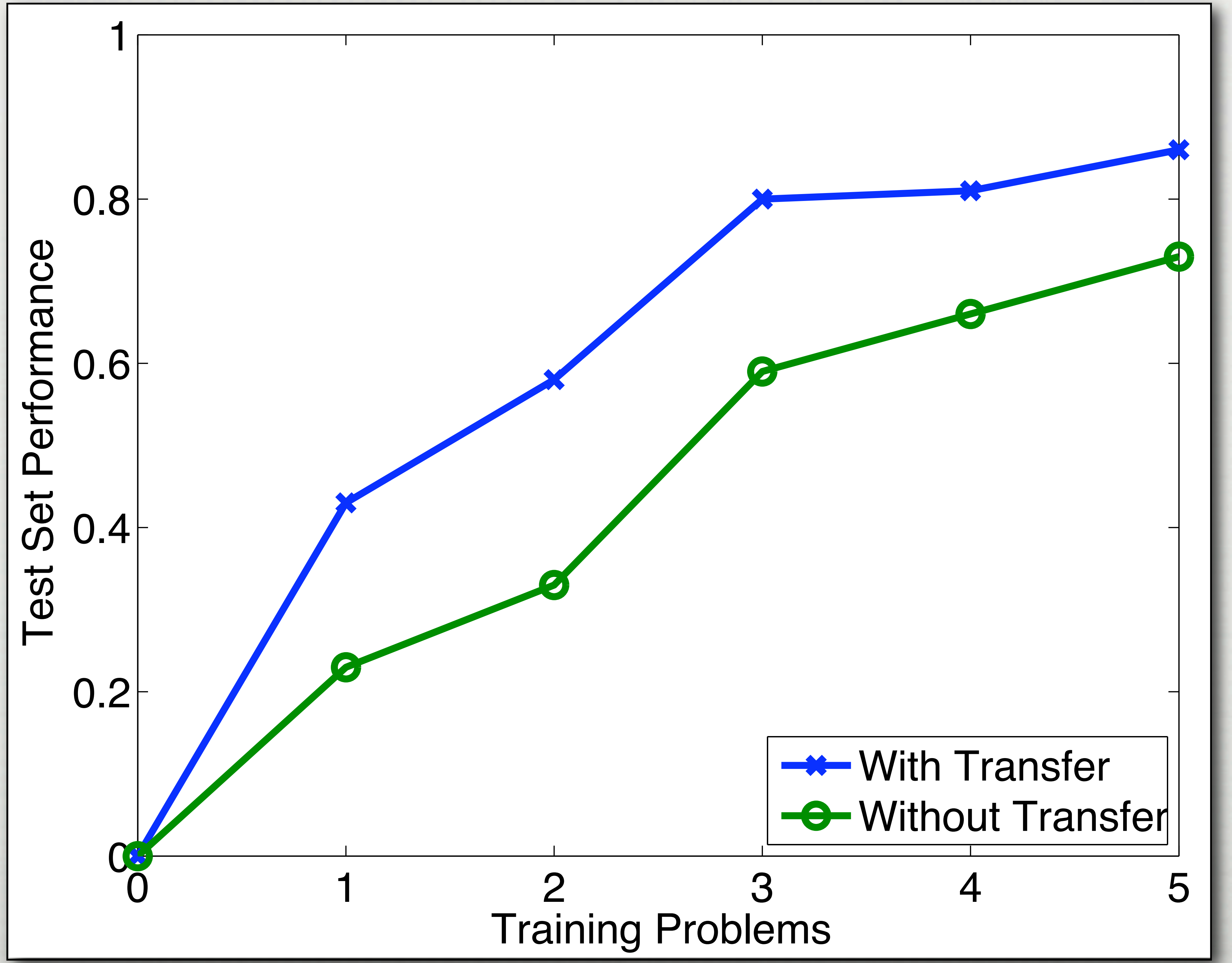
- Bistability in binocular rivalry
  - Distribution of dominance durations
  - Contextual bias, initial bias
  - Traveling waves
- Fusion (single false percept halfway between actual stimuli)

An Experiment with Bayesian Learning in SimStudent

- Bayesian grammar induction ***learns how to parse*** from examples
  - `4x - 2 = 3,  2x + 5 = 3x - 1`
  - learn grammar by ***approximate Bayesian inference***
    - *Inside-Outside* to parse training data w/ current grammar
    - *EM* to update parameters based on parse
    - *Greedy search* to propose new rules
- ***Nodes*** in learned parse tree become ***features*** for SimStudent to use in rule learning
- Two conditions: ***transfer*** (10 previous easier problems) or ***no transfer*** (weak features: character recognition only)

[Li, Cohen, Koedinger, Matsuda, 2010]

Results



1
0.8
0.6
0.4
0.2
0
Test Set Performance
0
1
2
3
4
5
Training Problems
With Transfer
Without Transfer

Summary

- SimStudent: a cognitive model of student learning & problem solving
- Current version based on ***production system*** and ***ILP***
- My prediction: better cognitive models from ***Bayesian reasoning*** in a ***production system based on probabilistic logic***
- Experiments on ***learning productions***, on ***MCMC and bistability/fusion***, and on ***grammar induction***
  - show: production system approach is plausible, Bayesian reasoning helps capture observed effects

Brain Models and Mental Disease

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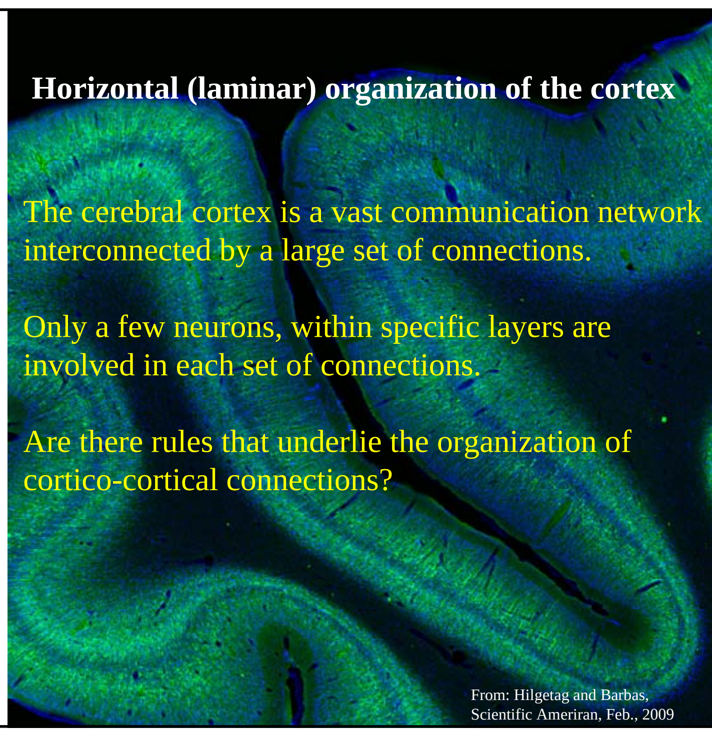
NSFcelest101510

Supported by grants from NSF, NIH (NIMH and NINDS), Autism Speaks, and NSF CELEST

Horizontal (laminar) organization of the cortex



The cerebral cortex is a vast communication network interconnected by a large set of connections.

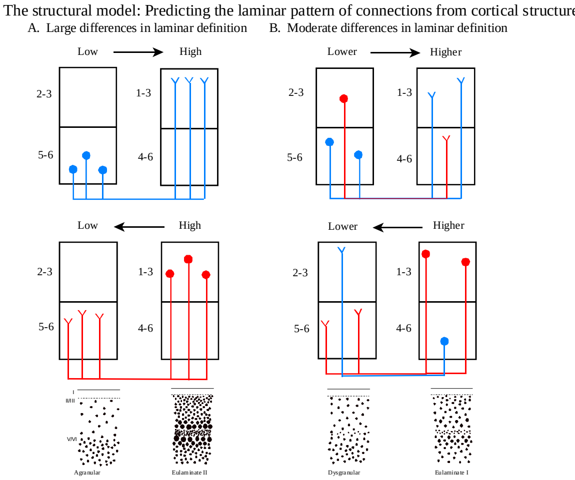
Only a few neurons, within specific layers are involved in each set of connections.

Are there rules that underlie the organization of cortico-cortical connections?

From: Hilgetag and Barbas, Scientific Ameriran, Feb., 2009

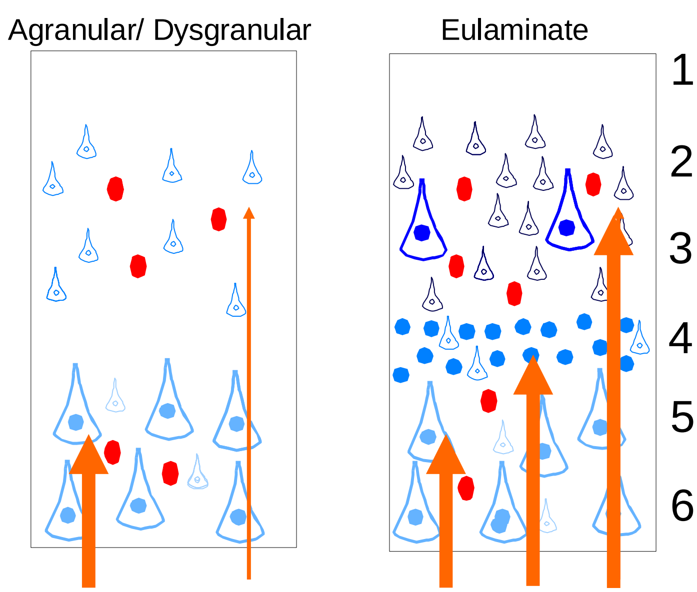
Predicting cortico-cortical connections from cortical structure: implications for normal function and psychiatric diseases

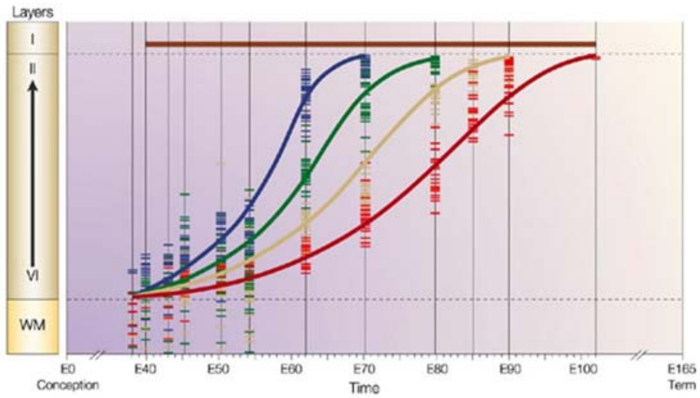
The structural model: Predicting the laminar pattern of connections from cortical structure



Adapted from: Barbas and Rempel-Clower, 1997

Hypothesis for Development



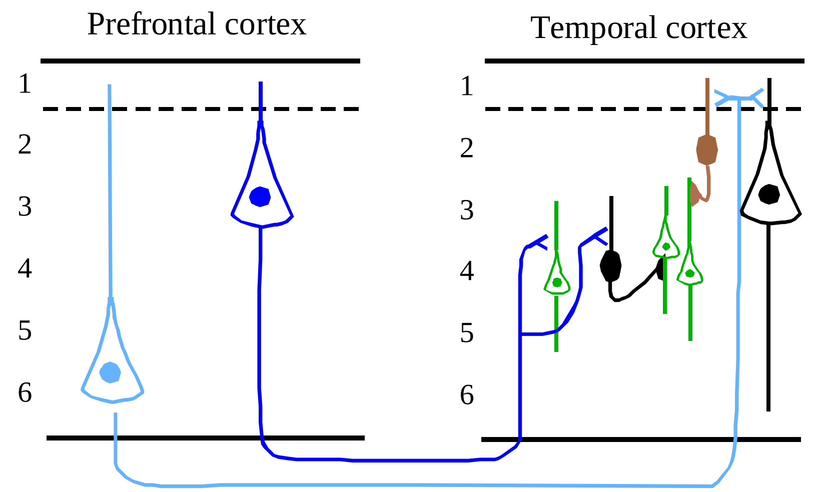


From Rakic, P. 2002 Nature Reviews | Neuroscience

Figure 2 | Relationship between the time of origin and the final position of cortical neurons in the macaque monkey. Representation of the positions of heavily labelled neurons in the four representative cytoarchitectonic cortical areas. Each monkey was injected with 10 mCi kg-1 of 3H-thymidine (3H-dT) on a selected embryonic day (E) and killed postnatally. A representation of the approximate position of layers I–VI and the white matter (WM) is on the left. Embryonic days are represented on the horizontal axis, starting with the beginning of the second fetal month (E34) and ending at term (E165). Positions of the vertical lines indicate the embryonic day on which an animal received a pulse of 3H-dT. On each vertical line, short horizontal markers indicate positions of the heavily labelled neurons encountered in a 2.5-mm-long strip of cortex. Blue, Brodmann area (BA) 24; green, BA 11; yellow, BA 46; red, BA 17. Layer I neurons in the primates are generated throughout the entire period of neurogenesis in each area (brown).

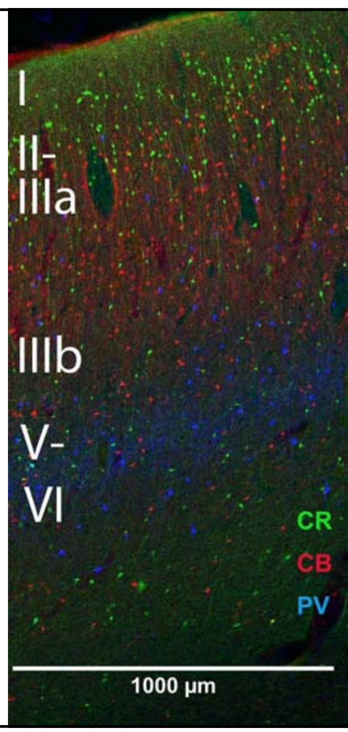
What is the significance of knowing the laminar origin and termination of connections?

Interaction of prefrontal pathways with excitatory and inhibitory systems: corticocortical connections



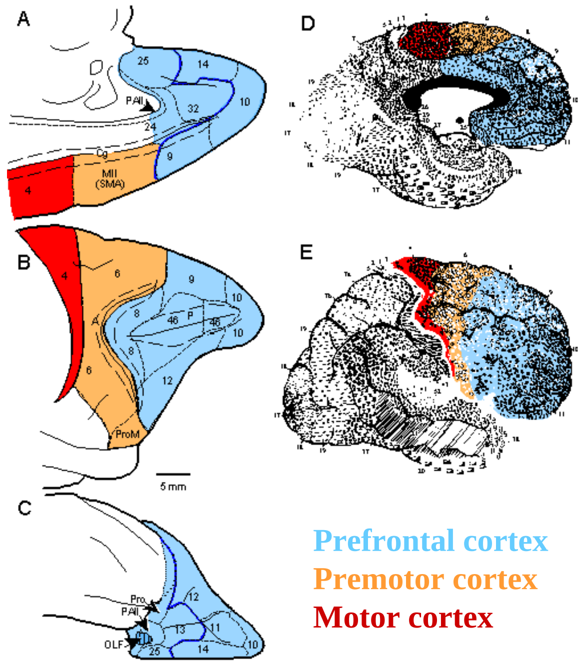
The microenvironment of the origin and termination of laminar-specific connections varies.

From Barbas, 2006

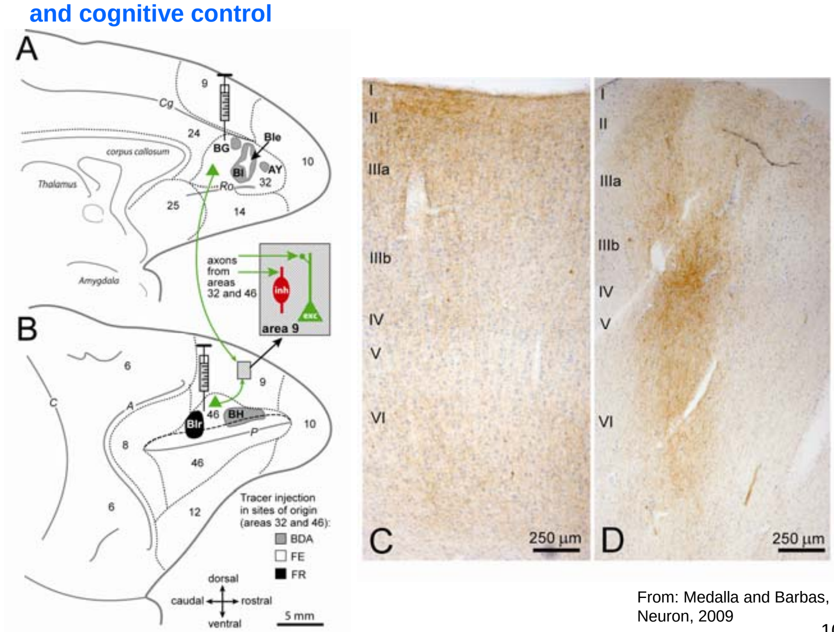


By Timbie, Clare
CELEST

Rhesus monkey Human

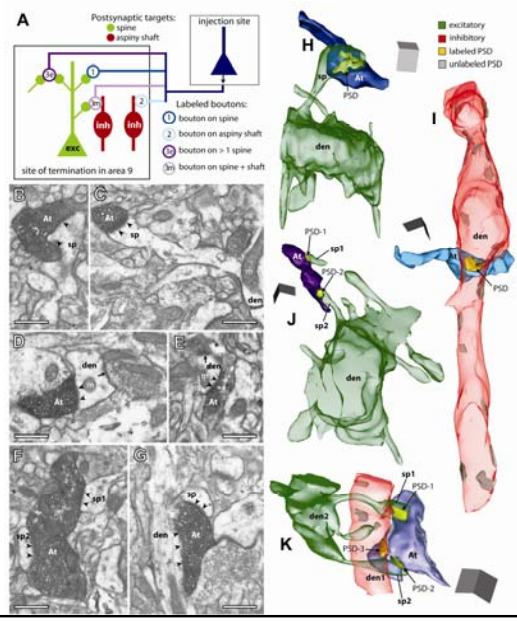


Synaptic interactions of prefrontal areas associated with attention and cognitive control



From: Medalla and Barbas, Neuron, 2009

Interaction of prefrontal pathways at the synaptic level



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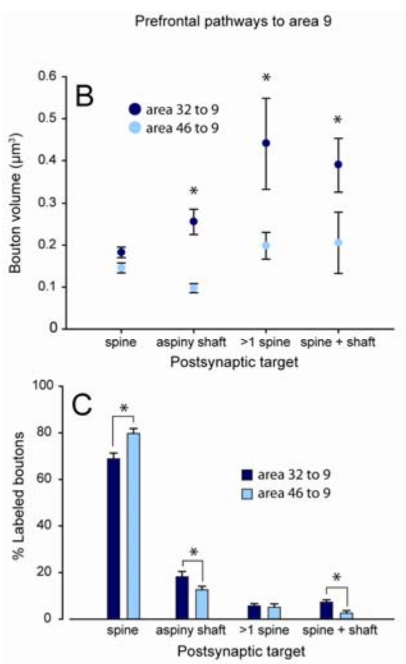
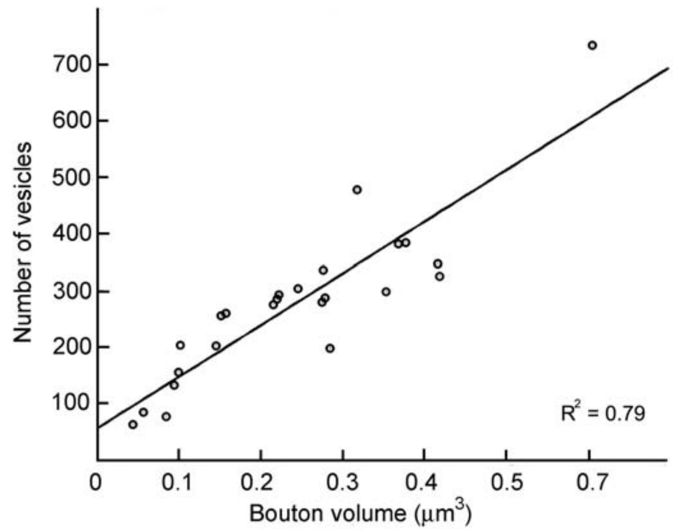


The ACC (area 32) targets more inhibitory sites in DLPFC (area 9), and the synapses are larger than the pathway linking two related areas (area 46 to 9).

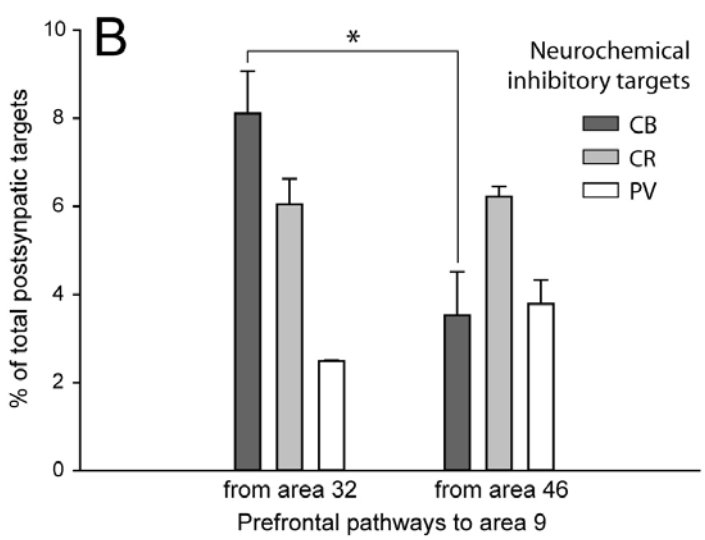
From: Medalla and Barbas, Neuron, 2009

Large boutons have more synaptic vesicles



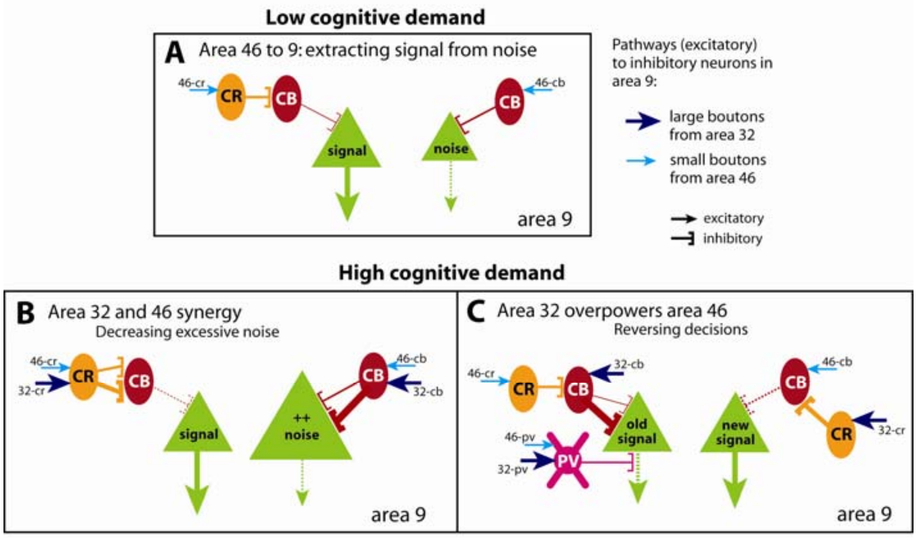
From: Germuska et al., 2006, Cerebral Cortex, 2006

The ACC targets preferentially CB inhibitory neurons, which are synaptically suited to reduce noise.



From: Medalla and Barbas, Neuron, 2009

Pattern of connection from ACC (area 32) to DLPFC area 9



From: Medalla and Barbas, Neuron, 2009

Common and distinct features of schizophrenia and autism:

Two sides of the same coin?

Schizophrenia and Autism

have their roots in development

Pathology in schizophrenia

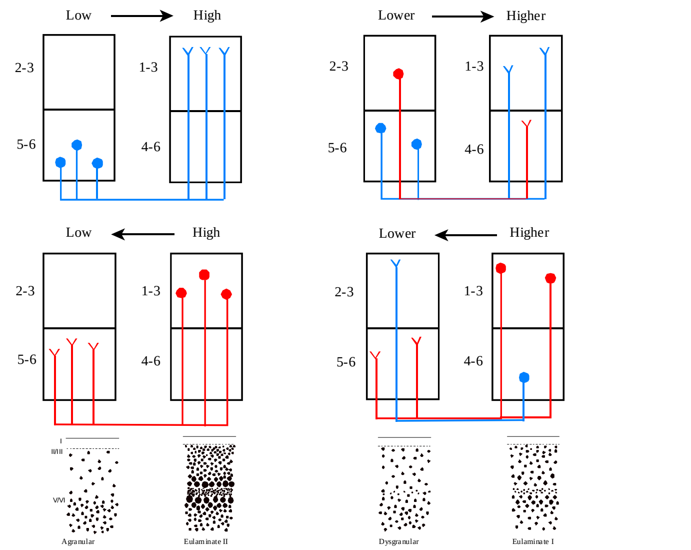
The number of pyramidal (excitatory) neurons is reduced in the deep layers of the anterior cingulate cortex (ACC) in schizophrenia (Benes et al., Biol. Psych., 50, 2001).

The deep layers of ACC project to the upper layers of dorsolateral prefrontal cortex.

Predicting cortico-cortical connections from cortical structure

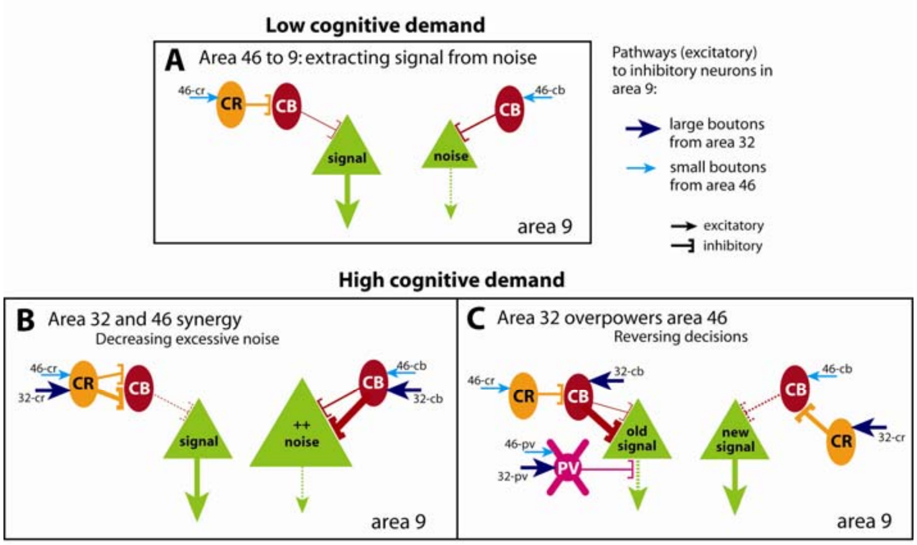
The structural model: Predicting the laminar pattern of connections from cortical structure

A. Large differences in laminar definition B. Moderate differences in laminar definition



Adapted from: Barbas and Rempel-Clower, 1997

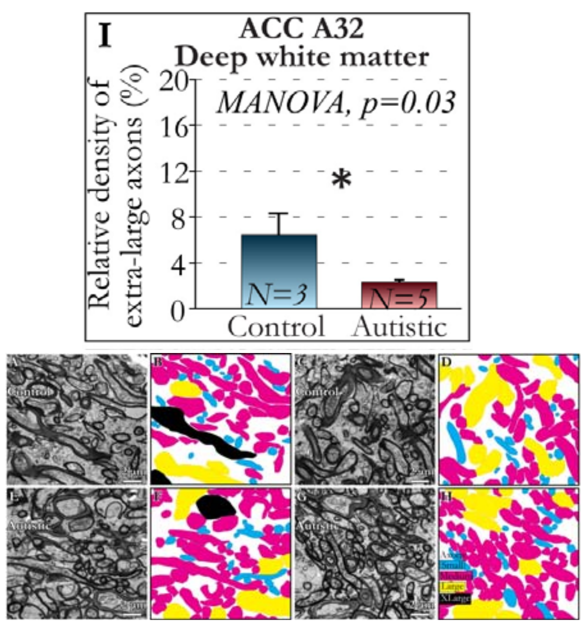
Pattern of connection from ACC (area 32) to DLPFC area 9: implications for schizophrenia



From: Medalla and Barbas, Neuron, 2009

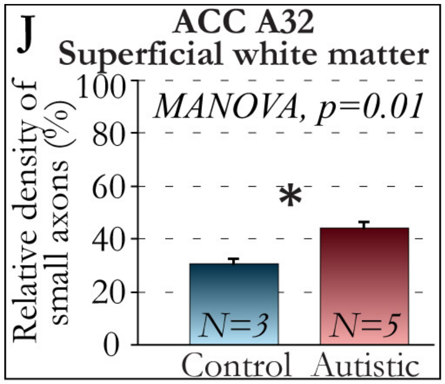
Circuit Abnormalities in Autism: the White Matter

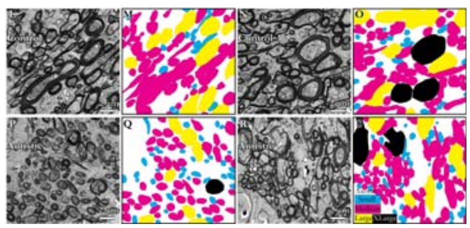
The white matter below the frontal lobe, and especially the ACC, is enlarged in the brains of children with autism relative to controls.



Deep white matter connects distant areas

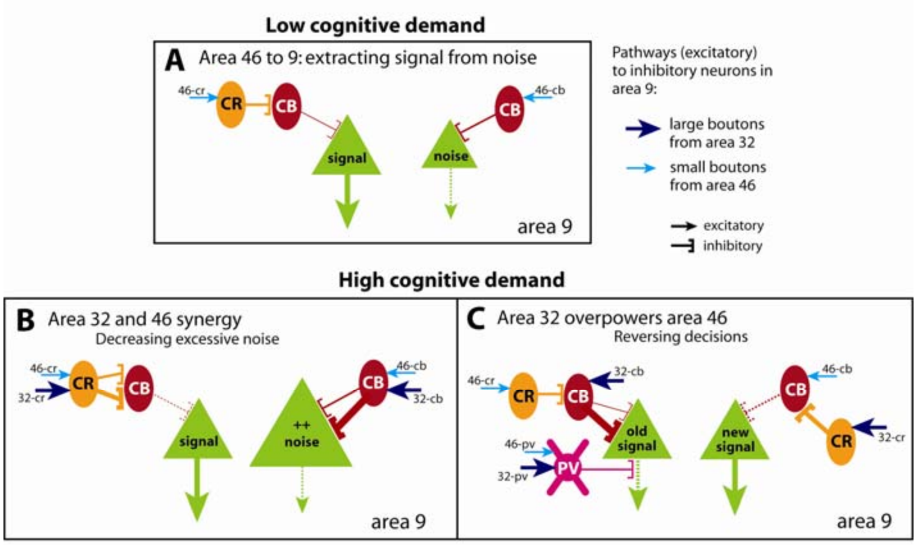
The autistic cases had fewer extra-large axons than normal controls





Superficial white matter connects nearby areas: Autistic brains had more small (thin) axons

Pattern of connection from ACC (area 32) to DLPFC area 9: implications for autism



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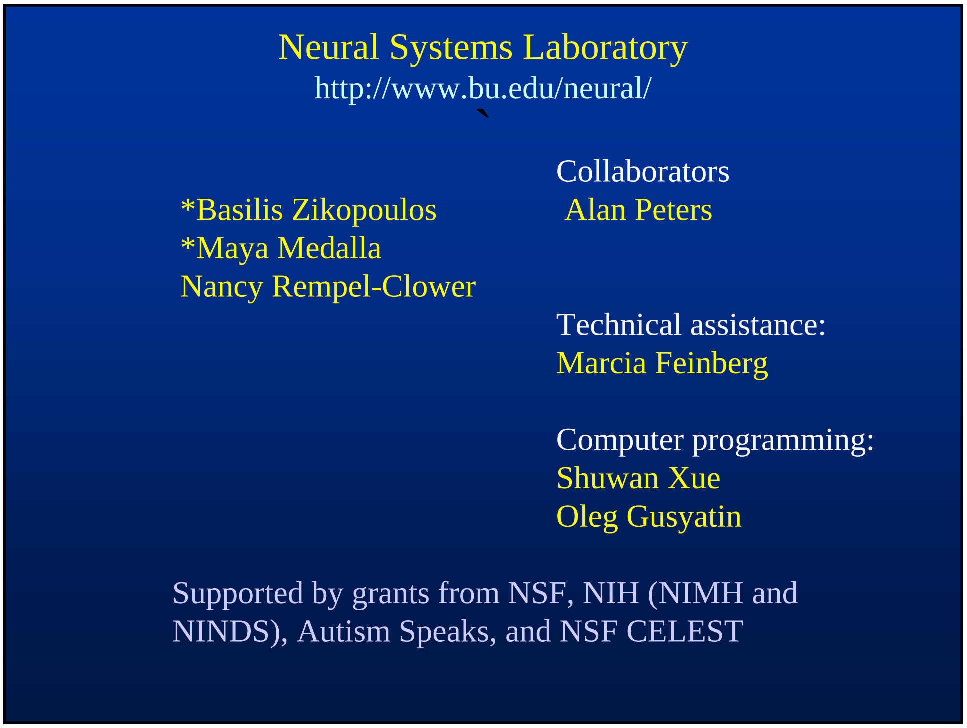
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